The Profit-Credit Cycle *

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Abstract

Bank profitability leads the credit cycle. An increase in return on equity of the banking sector predicts rising credit-to-GDP ratios in a panel of 17 advanced economies spanning the years 1870 to 2015. The pattern also holds in bank level data and is only partially explained by a balance sheet channel, where higher retained profits relax net worth constraints. Turning to alternative explanations, the results are consistent with behavioral credit cycle models in which agents extrapolate past defaults to expected future credit outcomes. Using recent US data, we show that survey-based measures of optimism and profitability expectations are tightly linked to past profitability, forecast credit growth, and display predictable forecast errors. These patterns are also reflected in aggregate cycles: increases in profitability not only predict credit expansions, but also elevated crisis likelihood a few years later.

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1. Introduction

The credit cycle takes center stage in the evolving narrative of the 2007/2008 crisis. The financial turmoil was preceded by a boom in private credit in many countries, just as so many other crises episodes before (Schularick and Taylor, 2012). More generally, the credit cycle also predicts medium-term output growth, but economic forecasters often fail to account for this relationship (Mian et al., 2017a). Asset return data suggest they are not alone: capital markets often neglect the treacherous link between credit expansions and downside risk (Baron and Xiong, 2017; Fahlenbrach et al., 2017; Krishnamurthy and Muir, 2017). In response to the output risks associated with credit expansions, policy-makers today monitor credit aggregates closely and apply a wide range of macro-prudential tools, once they detect overheating. While these policies are often effective in dampening credit growth (Akinci and Olmstead-Rumsey, 2018), they are rather a treatment of symptoms than causes. This is no surprise as the understanding of the ultimate sources of credit supply expansions is still limited (Mian and Sufi, 2018).

In this paper, we revisit the origins and turning points of the credit cycle. It is well documented that firms and managers overpredict future earnings when profits are high and that this has consequences for investment (Gennaioli et al., 2016; Greenwood and Hanson, 2015). We show that there is a similar pattern underlying bank lending. What we observe in the data is in fact a "profit-credit cycle". An increase in bank profitability predicts a credit expansion in the next three years, but also elevated crisis risk down the road. Crises occur once profits start reversing after a sequence of increases. These findings connect well with older ideas of "displacements" in the credit market triggering waves of optimism followed by a "Minsky moment" (Kindleberger, 1978; Minsky, 1977) and mesh nicely with new modeling approaches to the credit cycle based on extrapolative expectations (Bordalo et al., 2018b; Greenwood et al., 2018).

To study the profit-credit relationship, we collected a new dataset on bank profitability in 17 advanced economies, starting in 1870. The data allow us to systematically assess the relationship between bank profits, the credit cycle, and financial instability in modern financial history. The advantage of accounting profitability data is that they are, by definition, backward looking. In that sense, profits are distinct from credit spreads and stock prices, which are forward looking, and therefore can only help to assess whether future economic outcomes were anticipated. Krishnamurthy and Muir (2017) show for example that credit spreads are too low during the preceding boom, but anticipate the severity of a financial recession once the cycle has turned. For a subsample of countries and episodes we were able to further decompose bank profitability into its sources –

revenue, costs and loan losses – and its uses – funds paid out to shareholders and funds retained as equity in the balance sheet. Our new dataset is complemented by the data of the Macrohistory Database (Jordà et al., 2017b), which provides us with a chronology of banking crises and a large number of control variables for our investigation.

We find that bank profitability leads the credit cycle. High bank profits are followed by credit expansions. We measure profitability using the level of return on equity (RoE) and proxy a sequence of increasing or decreasing returns with the three-year change of this return ($\Delta_3 RoE$). A one standard deviation higher $\Delta_3 RoE$ predicts a 0.2 standard deviation higher change in credit-to-GDP over the subsequent three years. This relationship remains robust when we include additional controls, time effects and analyze subsamples. It holds for alternative measures of profitability or credit growth, during and outside of financial distress and on a country-by-country level.

Which mechanisms can explain the strong relationship between profits and the credit cycle? The timing of the relationship indicates that high bank profitability and credit cycles are unlikely to be linked through credit demand due to strong economic fundamentals. Credit demand factors would either create a positive contemporaneous correlation between profits and credit growth, or credit should expand in anticipation of higher future profitability when households and firms borrow today against high future income. However, profits and changes in profitability lead the credit expansion, and our data as well as Baron and Xiong (2017) show that credit expansions are followed by low rather than high subsequent returns. We distinguish further between demand and supply side explanations using the price of credit. A shift in credit demand should lead to higher interest rate spreads during the boom. We find the opposite. The price of credit (a corporate bond spread) is negatively associated with improvements in profitability.

The relationship could also be due to a net worth channel. High profits, if not paid out completely to shareholders, will increase net worth in the banking sector and thereby relax borrowing constraints (Bernanke and Gertler, 1989; Holmstrom and Tirole, 1997; Kiyotaki and Moore, 1997). In our long run data, we find evidence consistent with a net worth channel, where retained profits increase net worth and lending capacity. Bank capital predicts credit expansions, but the net worth channel is not able to explain the strong relationship we find in the data. We first show that the relationship between profits and future lending growth remains significant even in specifications that include the capital ratio and changes in banking sector capital as controls. In a second step, we rely on the idea that dividends paid to shareholders should be orthogonal to banks' borrowing constraints. Decomposing profits into dividends and retained earnings, we find a significant effect of dividend payments on future credit expansion, while controlling for retained earnings. Finally, we find that changes in profitability are related to credit expansions, even when we control for the level of RoE, that is the increase in funds that support additional borrowing. We conclude from these exercises that a net worth channel alone cannot fully account for the strong relationship between profits and subsequent credit developments.

We then assess if our results match the empirical predictions of expectations-based credit cycle models (Bordalo et al., 2018b; Greenwood et al., 2018). In these models, positive news – displacements in the language of Minsky (1977) – are extrapolated into the future and thereby trigger a wave of optimism. It is during these episodes that investors willingly supply credit, to be systematically disappointed in the following years. A moment of recognition unfolds in form of a rapid adjustment in expectations and prices, once there is a slowdown in the growth or a decrease of profitability. While these models focus on the bond market, we can apply the insights to bank lending. In that case, the prediction is that banks extrapolate from recently experienced loan default rates when building their expectations about future repayment. As a result, banks will be too optimistic when profits are high (loan losses are low) and vice versa. Optimism will be reflected in credit supply decisions and hence high profitability should be associated with credit expansions, in line with our main result. We use a decomposition of bank profitability into loan losses, revenues and costs, to study the mechanism in more detail. We find that decreasing loan losses are associated with expanding credit, while lower costs or higher revenues are not associated with subsequent credit growth.

Credit cycle models based on extrapolative expectations furthermore link increases in profitability and excess optimism to a reversal in expectations. We find that increases in profitability predict financial instability over horizons of more than two years, while the year prior to a banking crisis is often characterized by declining profitability. This result is consistent with the model of Bordalo et al. (2018b) where less favorable news after a series of good news lead to sharp reversals and also with models of bank runs that are linked to a perceived weakening of bank fundamentals (Goldstein and Pauzner, 2005). When we focus on the role of loan losses, we find that decreasing loan losses predict financial turmoil a few years ahead. These results mirror the behavior of credit spreads (Krishnamurthy and Muir, 2017) and stock market volatility (Danielsson et al., 2018), which have both been found to be particularly low in the prelude to a crisis. Similar to the findings in Baron and Xiong (2017), we find that bank equity investors are not compensated for these effects and high profitability is associated with low excess returns on the bank equity index over three to six years.

To study the expectation formation process in further detail, we use data from a survey among bank CFOs in the United States.[1] We find that measures of optimism and expected profitability are strongly associated with past profitability. The link between realized profitability and past developments is weaker, and as a result, bank CFOs make predictable forecast errors. When profits are high, bank CFOs are too optimistic and realized future earnings are lower than expected. In a similar way, bank CFOs are too pessimistic, when profits are low. We then show that expectations and optimism matter for decisions. Higher optimism today is associated with considerably more lending over the next 12 months. This creates a link between forecast errors and lending, implying that extrapolation could be associated with a misallocation of credit.

In a final step, we ask whether a similar mechanism is at work at the bank level. We would expect to find a link between increases in bank profitability and credit growth at the bank level, if bank managers or loan officers extrapolate based on their own or the bank's experiences. It has been shown that individual experiences matter for inflation expectations (Malmendier and Nagel, 2015) and financial risk taking (Malmendier and Nagel, 2011). We use call report data to study whether increases in profitability and loan losses are linked to credit expansion in a panel of US banks. Crucially, the bank level data allow us to include additional controls at the bank level and quarter fixed effects as a measure of the stance of the US economy, proxying for aggregate credit demand. We find a strong link between increases in profitability and credit growth, just as in our aggregate long-run data.

Our paper is related to three strands of research. One strand discusses patterns of the credit cycle (Aikman et al., 2015; Dell'Ariccia et al., 2016) and identifies markers that help to tell different kinds of credit booms apart (Gorton and Ordonez, 2019; Richter et al., 2017). A rapidly growing literature studies the relationship between credit and business cycles (Mian et al., 2017a) with a focus on credit supply based explanations. Financial deregulation can be linked to credit supply expansions in the United States in the 1980s (Mian et al., 2017b) and in the run-up to the recent crisis (Di Maggio and Kermani, 2017). Our results support the view that credit supply plays an important role in shaping the credit cycle.

Second, our paper extends the behavioral credit cycle literature. Evidence for overextrapolation of recent shocks or trends is pervasive. Greenwood and Shleifer (2014) show that survey-based investor expectations are extrapolative and hard to reconcile with rational expectations models. This pattern does not depend on the asset class or context. Similar results have been obtained analyzing macroeconomic expectations of professional forecasters (Bordalo et al., 2018a), households house price expectations (De Stefani, 2017; Kuchler

[1] Data start around the year 2000 and are obtained from the Duke CFO Global Business Outlook (2018)

and Zafar, 2019) and expectations in laboratory experiments (Landier et al., 2018). Recent research relates the extrapolation bias to fluctuations in real investment. Gennaioli et al. (2016) show that CFOs extrapolate past performance with the arising expectational errors explaining investment decisions on the firm level. A similar pattern drives boom and bust in shipbuilding as demonstrated by Greenwood and Hanson (2015).

Bordalo et al. (2018b) incorporate extrapolative biases in expectation formation into a model of the credit cycle. In their model creditors assign higher probabilities to states of the world that have become more likely in light of recent data, leading to excessive credit growth after a number of good realizations and to predictable reversals. In Greenwood et al. (2018) creditors extrapolate default risk. This generates an endogenous feedback mechanism between credit market outcomes and credit market sentiment and temporary disconnects between fundamentals and the credit cycle. Our results on the relation between loan losses and subsequent credit market outcomes are consistent with the key mechanism in this model.

It is important to note, that our data on bank profitability allow us to show that such a relationship holds for the bank credit cycle, while most previous studies focused on cyclical developments in the bond market (Greenwood and Hanson, 2013), or linked expansions in bank credit with data on prices and defaults from the bond market (Greenwood et al., 2018; Krishnamurthy and Muir, 2017). Linking bank profitability to bank credit is important, as the underlying theory of extrapolation most likely applies within a specific asset-class. Kuvshinov (2018) shows that measures of asset market overheating are not correlated across asset classes, so that extrapolation seems to be domain-specific.

Third, our paper is related to a literature that studies the relationship between net worth and credit in models with financial frictions (Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997). Holmstrom and Tirole (1997) analyze how net worth affects balance sheet debt capacity and lending of banks. All these models generate amplification of initial net worth shocks through the interplay of prices of collateralizable assets or income with borrowing constraints. A vast literature builds on these early contributions, studying alternative frictions, amplification mechanisms and integrating the mechanisms into sophisticated macroeconomic models (e.g. Brunnermeier and Sannikov, 2014). Empirically, Adrian and Shin (2010) show that banks adjust their balance sheets reacting to changes in net worth.

2. A new dataset on bank profitability

This paper is built around a novel long-run dataset on bank profitability across countries and time. We construct new return on equity and return on asset series for 17 countries from 1870 to today using banking sector balance sheets and income statements. So far, research with long-run historical data on credit cycles and systemic banking crises heavily relied on banking sector balance sheet information (Jordà et al., 2017a; Schularick and Taylor, 2012). A second strand of the literature recently started to incorporate market prices for debt and equity into the analysis (Baron and Xiong, 2017; Krishnamurthy and Muir, 2017). Banking sector income – in particular realized banking sector profitability – has been largely ignored. Adding accounting profits creates a natural link between the two strands of literature. The new dataset complements previous data collection efforts which provide us with a large set of macroeconomic and financial variables for our analysis (Baron and Xiong, 2017; Jordà et al., 2017a,b). Our main profitability series – return on equity (RoE) – is computed by dividing total profits of the banking system by book equity:

$$RoE = \frac{Net\ profits\ after\ Tax}{Book\ Equity} \tag{1}$$

The numerator of the equation measures accounting income of the banking system after the deduction of all relevant expenditures and corporate taxes. The denominator includes paid-in capital, reserves and retained earnings. The equity items also include profits carried forward and the issuance premium gained by selling stocks above their nominal value. Aside from the baseline profitability series, we also construct a return on asset series by dividing profits by total assets. However, due to important structural trends of this series, we focus in this paper on the return on equity series. Nevertheless, all main results hold when we use return on assets in the analysis.[2]

The data comes from a wide range of sources including publications of the OECD, central banks, banking supervisory institutions, work of banking historians and individual bank reports. The new series includes on average more than 130 years of data for each country in our sample. The paper is complemented by a detailed Data Appendix describing sources and data construction.

When constructing the profitability data, we combine micro and macro data. A large share of the dataset is based on aggregate banking statistics. In some countries, we need

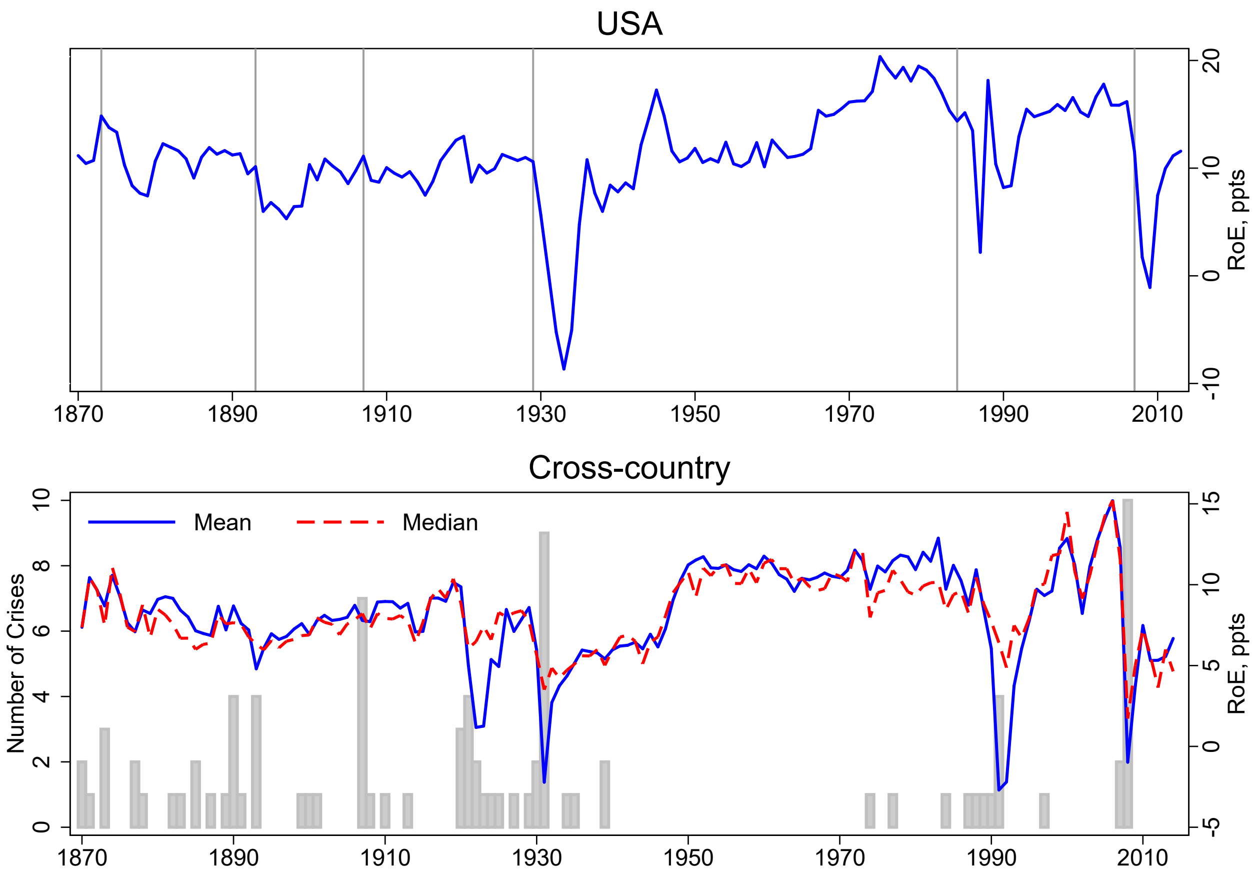
[2] Return on equity and return on assets are connected through the leverage ratio of the underlying financial institutions. Due to sampling and coverage differences, the implicit leverage ratio of the return on equity and return on asset series differs slightly from the leverage ratio of Jordà et al. (2017a).

to rely on data of individual large banks to extend the data back into the 19th century. Relying on data of a few banks might generate excess volatility compared to the banking sector statistics and add bank idiosyncrasies to the final series. However, in most cases the deviations are likely small, as the respective banking systems were dominated by a small number of banks (e.g. Canada) with a large market share. Our profit data might also be influenced by survivorship and selection bias. When not capturing the whole sector, our data typically relies on the biggest and most successful banks in a given country. Since we choose the banks based on their historic dominance and not based on their recent success or the survival until today, the survivorship bias is however unlikely to be large.

Another issue is related to the use of annual report data. We treat this data at face value. The sophistication of accounting standards and practice however varied significantly historically. As a consequence, the data might be distorted by profit smoothing and hidden reserves in bank balance sheets. We try to adjust the data whenever we find the appropriate means to do so. For example, Capie and Billings (2001) provide us with an updated series of banking sector profitability in the United Kingdom that accounts for transactions that involved hidden reserves in the balance sheet. Realized accounting losses may also lag the actual shock due to late realization and profit smoothing. Our empirical exercises, especially in the analysis of profitability during financial crises, reflect this possibility.

Figure 1 illustrates the data. It shows the *RoE* series for the United States and averages across the 17 countries in our database. The vertical lines in the US graph indicate banking crisis events and the grey bars in the cross-country graph indicate the number of countries with systemic banking crises in a given year. We rely on the narrative chronology by Jordà et al. (2017b) to identify systemic banking crises events. Several features stand out: Bank profitability, measured by RoE, was relatively stable over the last 145 years. The return on equity fluctuated around 8 percent in most countries (see also the summary statistics in Table B.2). In some countries – such as the United States – there is a gradual upward trend in return on equity in the second half of the 20th century. Major deviations from the trend follow or coincide with systemic banking crises. These crises often drive bank accounting profitability into deep negative territory. For example, the *RoE* series for the United States shows three major negative shocks with *RoE* around or below zero: the Great Depression, the S&L crisis and the Great Recession. The defining feature of the aggregate data are the extraordinarily low profits during clustered crisis events. Comparing profitability in crisis and non-crisis episodes reveals that *RoE* in a crisis-year is around 7% lower than the non-crisis average. However, not all systemic banking crises are characterized by pronounced negative profitability. While some crises nearly wiped out the entire banking sector capital, others are invisible in the profitability series (e.g. the crisis of 1907 in the United States).

Figure 1: *Long-run evolution of RoE in the United States and across sample countries*



Notes: This figure displays the evolution of *RoE* in % between 1870 and today for the USA and for a cross-country mean (median). Vertical bars indicate systemic financial crises in the US and the number of countries experiencing the start of a financial crisis respectively (see appendix for dates).

Our new dataset also allows us to decompose banking sector profits into sources and uses. Drawing from additional banking sector accounting information, we separate $RoE_{i,t}$ into a dividend and a retained earnings component. We define measures of dividends relative to equity DoE and retained earnings as a share of equity $REToE$. Since we do not observe retained earnings directly, we proxy for $REToE$ using the residual of profits and dividends. Furthermore, we were able to obtain information on the sources of bank profitability. We decompose profits into revenues (net interest plus net fee income), operating costs and loan losses.

In addition to the level of the profitability variable, we also compute 3-year changes in profitability variables as a proxy for medium-term changes:

$$\Delta_3 RoE_{i,t} = RoE_{i,t} - RoE_{i,t-3}. \tag{2}$$

As there are no clear trends in RoE over our sample period, this variable is on average close to zero. The standard deviation is around 7%, so three-year changes in RoE can be quite sizable. The bank profitability data is often dominated by extreme loss events during crises (see Figure B.1). We therefore winsorize all profitability measures at the 2.5% level. Detailed summary statistics for the winsorized and the raw data can be found in Table B.2. All main results of the paper hold in the raw data with the same significance level and slightly lower point estimates. Our main dependent variable is the change in the credit-to-GDP ratio over a three-year interval between time t and time $t+3$ (as in Mian et al., 2017a and Baron and Xiong, 2017):

$$\Delta_3 y_{i,t} = (Credit/GDP)_{i,t} - (Credit/GDP)_{i,t-3} \tag{3}$$

Credit here refers to bank credit extended to the domestic private non-financial sector. It includes loans to households as well as loans to non-financial firms. In contrast to profitability measures, there has been an upward trend in the ratio of credit to GDP over the past 150 years and $\Delta_3 y_{i,t}$ is around 2.3% on average.

3. Bank profitability and the credit cycle

This section studies the relationship between bank profitability and credit expansions. We establish that high or rising bank profitability is a significant and robust predictor of subsequent credit expansions. The analysis relies on the two previously defined profit measures, the level of RoE and the change $\Delta_3 RoE$. We assess the medium-term relationship with three-year changes in the ratio of bank loans to GDP ($\Delta_3 y_{i,t+3}$) as the dependent variable. Following the approach in Mian et al. (2017a) we estimate variants of equations

$$\Delta_3 y_{i,t+3} = \alpha_i + \beta^{\Delta RoE} \Delta_3 RoE_{i,t-1} + \sum_{\tau=1}^{3} \gamma_\tau \Delta y_{i,t-\tau} + \eta X_{i,t-1} + \theta Z_{i,t-1} + u_{i,t+3}, \tag{4}$$

and

$$\Delta_3 y_{i,t+3} = \alpha_i + \beta^{RoE} RoE_{i,t-1} + \sum_{\tau=1}^{3} \gamma_\tau \Delta y_{i,t-\tau} + \eta X_{i,t-1} + \theta Z_{i,t-1} + u_{i,t+3}, \tag{5}$$

where we include lagged changes $\Delta_3 RoE_{i,t-1}$ and levels $RoE_{i,t-1}$ and three yearly lags of the dependent variable ($\sum_{\tau=1}^{3} \Delta y_{i,t-\tau}$). $X_{i,t-1}$ is a vector of macrocontrols including three lags of real GDP growth, the level of real GDP as well as three lags of short term interest

Table 1: *Multivariate models for changes in credit-to-GDP, baseline specification*

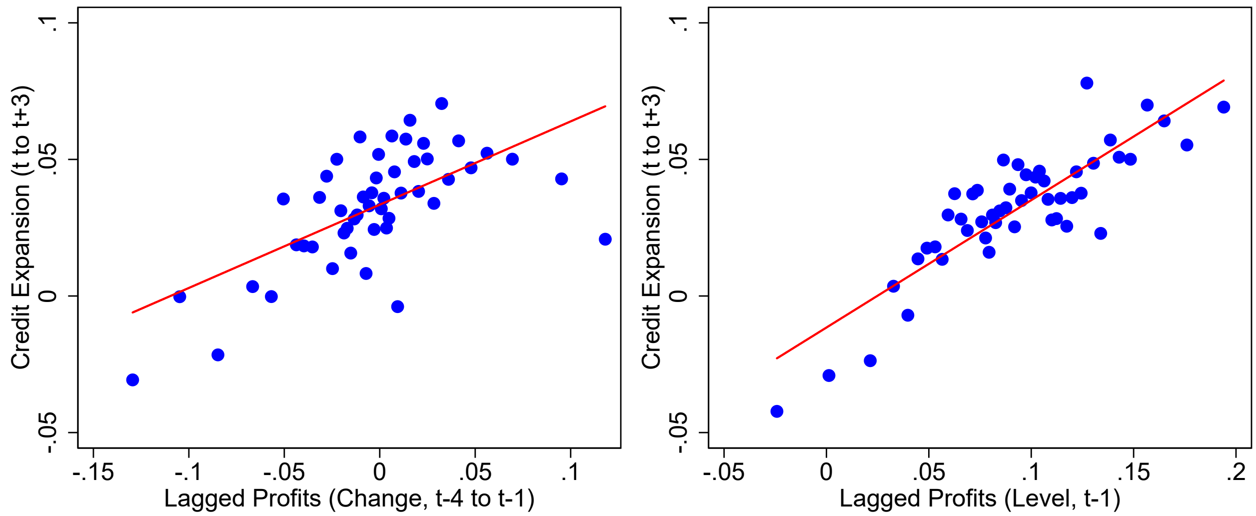
	Dependent variable: $\Delta_3 y_{it+3}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 RoE_{i,t-1}$	0.39***	0.34***	0.33***			
	(0.06)	(0.04)	(0.04)			
$RoE_{i,t-1}$				0.50***	0.47***	0.46***
				(0.08)	(0.09)	(0.09)
$Capital\ Ratio_{i,t-1}$			0.23***			0.24**
			(0.09)			(0.10)
$\Delta_3(Capital/GDP)_{i,t-1}$			0.17			-0.01
			(0.24)			(0.23)
Country fixed effects	✓	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓	✓
Macrocontrols		✓	✓		✓	✓
R^2	0.06	0.11	0.12	0.10	0.15	0.16
Observations	1611	1463	1462	1646	1494	1486

Notes: This table reports regressions of credit-to-GDP changes from t to $t+3$ on $RoE_{i,t-1}$ and $\Delta_3 RoE_{i,t-1}$. All specifications control for three lags of credit-to-GDP changes. Columns (2) and (5) add a vector of macroeconomic control variables described in the text. Columns (3) and (6) additionally control for net-worth channel proxies. All specifications include country fixed effects. Standard errors in parentheses are dually clustered on country and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

rates, long term interest rates, inflation, and the current account-to-GDP ratio. As a second set of controls ($Z_{i,t-1}$), and a first step towards disentangling possible channels, we add two proxies that may account for a net worth channel: the lagged capital ratio of the banking sector and three-year changes in bank capital relative to GDP.

Table 1 column (1) shows that an increase in profitability over the past three years ($\Delta_3 RoE_{i,t-1}$) predicts significantly higher credit expansion ($\Delta_3 y_{i,t+3}$). A similar result emerges when we include the lagged level $RoE_{i,t-1}$ in column (4). Banks extend more credit when measures of realized profitability look good. Adding macroeconomic controls in (2) and (5) reduces the coefficients slightly, but the results remain highly significant. In (3) and (6) of Table 1 we add the capital ratio as a control for balance sheet constraints in the banking sector. Adrian and Shin (2010) have argued that book leverage ratios measure net-worth constraints in the banking sector. Consistent with a net worth channel, we find that high capital is associated with increases in the credit-to-GDP ratio over the following years – relaxed funding constraints are associated with increased lending. However, including the capital ratio and a measure of the increase in aggregate capital, does not affect the results for the profitability measures.

Figure 2: *Binned scatterplot for the relationship between profitability and credit-to-GDP changes*



Notes: The figure relates bank profitability and subsequent three-year changes in credit to GDP. Observations are collapsed into 50 equal sized bins according to their profitability. Each point represents the group specific means of profitability and credit expansion after controlling for the vector of net-worth and macroeconomic variables from the regressions described in the text. Fitted regression lines illustrate the correlation between bank profitability and subsequent credit expansion.

How sizable are these effects? Increasing $\Delta_3 RoE_{i,t-1}$ ($RoE_{i,t-1}$) by one standard deviation is associated with increases in $\Delta_3 y_{i,t+3}$ of about 0.17 (0.25) standard deviations or, as a more tangible benchmark, with a 1.46% (2.21%) increase in credit-to-GDP over a three-year window. The sample mean of $\Delta_3 y_{i,t+3}$ is 2.3% as the size of the financial sector has been increasing over the past 150 years. Our estimates imply, that this growth rate increases by two thirds, when realized profitability growth is elevated by one standard deviation.

Figure 2 presents scatterplots corresponding to the above specifications using levels and changes in profitability. In both cases, the data are collapsed into 50 bins according to lagged changes or levels of profitability and the graph displays the mean for observations in each of these bins. On the y-axis, the mean of three-year credit-to-GDP changes for each of the 50 groups is presented. The graph shows the relationship of residuals after controlling for variation explained by the covariates included in the regressions. The fitted lines display a strong positive correlation between profit and credit variables, confirming the regression results.

3.1. Robustness of the main result

Subsamples: In Table 2 we look at subsamples of the data. All specifications include the full set of macro and net-worth control variables from the previous specifications. In a first step we restrict the sample to the post Bretton-Woods era to understand whether the strong relationship can also be observed in the current international monetary framework. We find that the results are robust to restricting the analysis to this time period. The same is true in a subsample of pre-2000 data, which we analyze to ensure that the relationship was not only a feature of the credit cycle that found a sudden end in the 2007/2008 crisis. In column (3), we use non-overlapping windows of observations in the dependent variable to deal with autocorrelation introduced through overlapping data and results remain highly significant. One concern may be that the results are mostly driven by the behavior of profitability and credit around financial crises events. To address this issue we exclude in column (4) a 5-year window around financial crises from the sample. We find again that the results are robust and remain highly significant. Finally, in column (5), we address possible cross-country correlation of variables and include year-fixed effects. The year fixed effects increase the R^2 to around 0.3 in both cases, indicating that there is a high degree of cross-country correlation in credit expansion, as identified in other studies (Jordà et al., 2019; Rey, 2016). The coefficients on profitability measures remain however highly significant.

Crisis observations: While we exclude crisis observations in one of the previous exercises, we can also ask whether profitability matters within a crisis. In Table A2.12 we include one observation for each financial crisis episode. We deviate slightly from our previous timing assumption and define time τ as the year after a financial crisis started and our dependent variable is $\Delta_3 y_{i,\tau+3}$. We then ask whether higher RoE_τ and $\Delta_3 RoE_\tau$ are associated with stronger recovery of credit-to-GDP in the years following the crisis. The coefficients are positive and highly significant, suggesting that losses during a crisis play an important role for the recovery of credit.[3]

Alternative credit measures: The appendix presents further robustness tests with respect to variable definitions. In a first step, we vary the dependent variable. So far, $\Delta y_{i,t+3}$ referred to the three-year change in the credit-to-GDP ratio. In Table A1.1 we replace credit-to-GDP with logged real private credit per capita to rule out the possibility that the effect is driven by the denominator. The results are in line with our previous findings. In Table A1.2 we move away from credit variables and look at the bank-assets-to-GDP ratio. The findings are similar to those for credit variables. In Table A1.3 we ask whether the

3 However, the losses are often recognized with a delay of one year. Hence, the slightly adjusted timing in this exercise.

Table 2: *Multivariate models for changes in credit-to-GDP, subsamples and time effects*

	Dependent variable: $\Delta_3 y_{it+3}$				
	(1) Post-1973	(2) Pre-2000	(3) Non-overlap	(4) No-crisis	(5) Year effects
$\Delta_3 RoE_{i,t-1}$	0.25^{***}	0.31^{***}	0.30^{***}	0.18^{***}	0.16^{***}
	(0.07)	(0.05)	(0.09)	(0.04)	(0.04)
Country fixed effects	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓
Control variables	✓	✓	✓	✓	✓
Exclude 5-year crisis window				✓	
Year effects					✓
R^2	0.22	0.11	0.17	0.15	0.31
Observations	640	1275	484	1207	1462
	Dependent variable: $\Delta_3 y_{it+3}$				
	(1) Post-1973	(2) Pre-2000	(3) Non-overlap	(4) No-crisis	(5) Year effects
$RoE_{i,t-1}$	0.53^{***}	0.36^{***}	0.43^{***}	0.33^{***}	0.31^{***}
	(0.10)	(0.10)	(0.08)	(0.08)	(0.07)
Country fixed effects	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓
Control variables	✓	✓	✓	✓	✓
Exclude 5-year crisis window				✓	
Year effects					✓
R^2	0.26	0.13	0.21	0.17	0.32
Observations	643	1299	493	1225	1486

Notes: This table reports regressions of credit-to-GDP changes from t to $t+3$ on $RoE_{i,t-1}$ and $\Delta_3 RoE_{i,t-1}$. All specifications control for three lags of credit-to-GDP changes and a vector of net-worth and macroeconomic control variables (see text in section 3). Column (1) uses only post-1973 data. Column (2) uses only pre-2000 data. Column (3) uses non-overlapping windows of three-year credit expansion. Column (4) excludes centered 5-year windows around financial crises. Column (5) includes year-fixed effects. Standard errors in parentheses are dually clustered on country and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

relationship is similar for non-credit assets. Here, we find weaker results, so the mechanism seems to be more relevant for credit expansion than for other asset classes.

Alternative profit measures: Furthermore, the appendix also shows results for different definitions of the explanatory variables. In particular, a concern may be that the results are due to bank capital in the denominator of RoE. In Table A1.5 and Table A1.7 we vary the denominator and normalize profits by GDP or by total assets and find that results hold. Furthermore, the results are also robust, when we replace RoE with the log of real bank profits in Table A1.6.

Profitability surprises: For changes in profitability to affect expectations, these changes must have been unanticipated. Since we have no direct measure of unexpected profitability changes, we use a regression approach and clean the profitability series from expected changes. We first run a regression to explain changes in profitability with mean reversion in profitability (that is including past changes and levels of returns) and with shareholder expectations expressed through returns on the bank equity index. Shareholder return data is from (Baron and Xiong, 2017). The results for this regression are shown in Table A1.8. We then use lagged residuals from this regression as a measure of past profit surprises and re-estimate our baseline specifications. The results are presented in Table A1.9 and qualitatively similar to our previous results. The coefficients cannot be directly compared as we use three-year changes in RoE in the baseline and the approach here provides us with residual changes over a one year horizon. We will study the role of expectations in more detail in section 6.

Country level evidence: In Figure A1.1 we plot the coefficients at the country level. We run a time series regression of $\Delta_3 y_{i,t+3}$ on lagged profitability measures for all our sample countries one by one. The graphs show that the coefficients are significantly positive in a majority of countries, so that the strong association between profitability and credit expansion seems to be a common feature in all our sample countries.

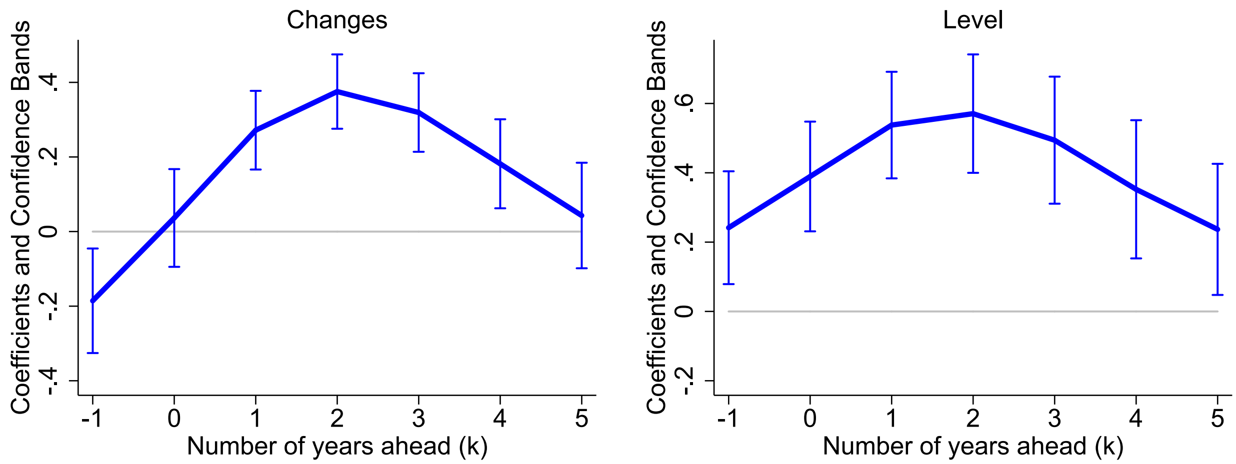
3.2. Timing

We now extend the baseline setup and describe the dynamic relationship between profitability measures and the change of the credit-to-GDP ratio over varying 3-year windows (similar to Mian et al., 2017a). Remember, $\Delta_3 y_{i,t}$ refers to the change in the credit-to-GDP ratio between $t-3$ and t. In the following equation, the RHS of the equation is held constant, while we shift the dependent variable $\Delta_3 y_{i,t+k}$ in time:

$$\Delta_3 y_{i,t+k} = \alpha_i + \beta \Delta_3 RoE_{i,t-1} + \eta X_{i,t-1} + \theta Z_{i,t-1} + u_{i,t+k} \tag{6}$$

where $k = -1, 0, ..., 5$ and we replace $\Delta_3 RoE_{i,t-1}$ with $RoE_{i,t-1}$ in the levels specifications. The results are shown in Table 3. In the tables, going from left to right, we vary k from -1 to 5. This means that the right hand side of Equation 6 remains fixed and in subsequent columns we report the results for a shift of the dependent variable one year further into the future. In the changes specification Equation 6, this means that column (1) of Table 3 ($k = -1$) assesses the relationship between changes in profitability from $t-4$ to $t-1$ and

Figure 3: *Multivariate models for changes in credit-to-GDP, dynamic relationship*



Notes: This figure displays coefficients from estimating Equation 6 for $k = -1, 0, ..., 5$. See Table 3 for more information. Standard errors are dually clustered on country and year. Bars denote 95% confidence intervals around the coefficient estimates.

Table 3: *Multivariate models for changes in credit-to-GDP, dynamic relationship*

	Dependent variable: $\Delta_3 y_{it+k}, k = -1, 0, ..., 5$						
	(1) $\Delta_3 y_{i,t-1}$	(2) $\Delta_3 y_{i,t}$	(3) $\Delta_3 y_{it+1}$	(4) $\Delta_3 y_{it+2}$	(5) $\Delta_3 y_{it+3}$	(6) $\Delta_3 y_{it+4}$	(7) $\Delta_3 y_{it+5}$
$\Delta_3 RoE_{i,t-1}$	-0.19***	0.04	0.27***	0.38***	0.32***	0.18***	0.04
	(0.07)	(0.07)	(0.05)	(0.05)	(0.05)	(0.06)	(0.07)
Country fixed effects	✓	✓	✓	✓	✓	✓	✓
Control variables	✓	✓	✓	✓	✓	✓	✓
R^2	0.25	0.19	0.16	0.14	0.11	0.07	0.06
Observations	1387	1374	1360	1345	1331	1316	1300
	Dependent variable: $\Delta_3 y_{it+k}, k = -1, 0, ..., 5$						
	(1) $\Delta_3 y_{i,t-1}$	(2) $\Delta_3 y_{i,t}$	(3) $\Delta_3 y_{it+1}$	(4) $\Delta_3 y_{it+2}$	(5) $\Delta_3 y_{it+3}$	(6) $\Delta_3 y_{it+4}$	(7) $\Delta_3 y_{it+5}$
$RoE_{i,t-1}$	0.24***	0.39***	0.54***	0.57***	0.49***	0.35***	0.24**
	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)	(0.10)	(0.10)
Country fixed effects	✓	✓	✓	✓	✓	✓	✓
Control variables	✓	✓	✓	✓	✓	✓	✓
R^2	0.26	0.24	0.22	0.20	0.15	0.10	0.08
Observations	1405	1393	1380	1365	1351	1336	1320

Notes: This table presents results from estimating Equation 6 for $k = -1, 0, ..., 5$. Each column gradually leads the left-hand-side variable by one year. All specifications control for a vector of net-worth and macroeconomic control variables (see text in section 3). Standard errors in parentheses are dually clustered on country and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively the change in the credit-to-GDP ratio between $t-4$ and $t-1$. $k=3$ is equivalent to our previous specification. We include the full set of controls except the three lags of $\Delta y_{i,t}$ (for $k=-1$ the dependent variable is a linear combination of these).

The results in column (1) show that changes in credit-to-GDP and RoE are contemporaneously negatively correlated. Importantly, the relationship is reversed in the medium run: In column (5) we see that changes in RoE between $t-4$ and $t-1$ are positively associated with credit growth between t and $t+3$. The effect is strongest for $k=2$ and $k=3$ and the coefficients become smaller for larger k. The lower panel of Table 3 shows the relationship between profit levels and varying windows of 3-year changes in the credit-to-GDP ratio. A positive and significant relationship is visible at all horizons. However, the size of the coefficient increases over time. Especially in the medium term ($k=1$ to $k=3$) higher levels of current profitability predict positive changes in the credit-to-GDP ratio. The size of the coefficient peaks at $k=2$ and decays afterwards, much like the $\Delta_3 RoE$ results.

The dynamic relationship between profitability displays a distinguished pattern: a "profit-credit cycle". This relationship is visualized in Figure 3. The right panel displays coefficients for the level of profitability and the left panel for changes in profitability. Both graphs display an inverted u-shaped relationship, that is the response of the credit-to-GDP ratio to variation in profitability measures is strongest over the three years after profitability has been observed. This timing is inconsistent with credit demand explanations. If credit demand was the driver of the relationship, we would have expected to observe increases in credit-to-GDP against good current and future prospects. In that case changes in profitability and credit growth should display a positive contemporaneous correlation or, if households and firms borrow against anticipated good future fundamentals, credit expansion should lead profitability. We find exactly the opposite.

4. Net worth channel and behavioral credit cycles

This section studies the mechanism that links bank profitability and credit growth in further detail. First, we present additional evidence in favor of the hypothesis that bank profitability triggers expansions in credit supply. We then distinguish between different credit supply channels. We show that the relationship cannot be fully explained by net worth constraints of financial intermediaries. Instead, we find evidence consistent with an expectations -based mechanism. In a final step, we decompose profitability into revenue, costs and loan losses to compare the behavioral credit cycle explanation to other common narratives of credit expansion.

Table 4: *Multivariate models for changes in credit spreads*

	Dependent variable: *Bond Spread*$_{it}$		
	(1)	(2)	(3)
$\Delta RoE_{i,t-1}$	-0.41* (0.23)	-0.36** (0.17)	-0.34** (0.17)
Country fixed effects	✓	✓	✓
3 lags of y	✓	✓	✓
Macrocontrols		✓	✓
Net-worth controls			✓
R^2	0.43	0.46	0.46
Observations	993	993	993

Notes: This table reports regressions of credit spreads in t on lagged changes in profit. All specifications control for three lags of bond spreads. Column (2) adds a vector of macroeconomic control variables, column (3) additionally includes net-worth controls (see text in section 3). All specifications include country fixed effects. Standard errors in parentheses are dually clustered on country and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

4.1. Credit demand and supply

We have established that credit expansions follow high or increasing bank profitability. This relationship could be due to an increase in the supply of credit or due to higher demand for credit. The timing of the profit-credit relationship makes credit demand an unlikely explanation for the relationship (see subsection 3.2). A simple test can help to distinguish further between these two explanations. More specifically, supply and demand based explanations yield conflicting predictions regarding the price of credit during a credit expansion. If higher bank profits (i.e. lower loan losses) are associated with increases in credit demand and credit supply remains fixed, the price of credit should increase following increases in profitability. If the effect of bank profits on lending is due to increased credit supply and demand is constant, the price of credit should go down after an increase in profitability. We will use data on bond spreads (from Kuvshinov, 2018) as a measure of the price of credit to test these hypotheses. Credit spreads are a forward looking variable and profitability news should be incorporated quickly in the price. We will therefore analyse the relationship between spreads and lagged one-year changes in profitability instead of using the three-year changes. In our baseline specification, we control for three lags of credit spreads and additionally include country fixed effects:

$$y_{i,t} = \alpha_i + \beta^{\Delta RoE} \Delta RoE_{i,t-1} + \sum_{\tau=1}^{3} \gamma_\tau y_{i,t-\tau} + u_{i,t}. \tag{7}$$

The results are presented in column (1) of Table 4. The price of credit is negatively associated with changes in profitability. In combination with our baseline result, namely an expansion of credit, this suggests that credit supply is expanding. The result is robust to adding the vector of net-worth and macroeconomic controls as can be seen in columns (2) and (3). This finding corroborates earlier work on supply driven credit cycles (Krishnamurthy and Muir, 2017; Mian et al., 2017a).

4.2. Disentangling net-worth and expectation components

This section sets out to distinguish between a net worth and an expectations channel. We employ two different approaches. First, we decompose return on equity into retained earnings over equity (*RIoE*) and dividends over equity (*DoE*). Dividends paid out to shareholders are not available in the bank as net worth to relax borrowing constraints. We can hence use *DoE* as a measure of profitability that is unrelated to changes in net worth, while it affects expectations about future profitability when there is extrapolation. Applying this insight, the results in columns (1) to (4) confirm that the link between profits and credit expansion goes beyond the net worth channel. Columns (1) and (2) show that the growth in *DoE* over the previous three years is a predictor of credit expansion over the next three years. Similarly, the lagged level of *DoE* helps to forecast three-year credit expansion (see Table A1.10). In Columns (3) and (4) we also include the three-year change in retained earnings in the regression. The coefficient for $\Delta_3 DoE_{i,t-1}$ remains highly significant. Hence, changes in dividends are a significant predictor for bank credit expansion even when controlling for the component of profitability that is retained in the banking system and that directly relaxes future borrowing constraints. But we find also evidence for a net worth channel, the coefficient for retained earnings is positive and significant.

In a second step, we include the profitability level and the 3-year change in profitability together in one specification. Holding the level of profitability fixed, $\Delta_3 RoE$ is a proxy for the path the banking sector took to arrive at a certain level of profitability. In models of extrapolation, this path will affect expectations and these will be more optimistic when profits were increasing. Columns (5) and (6) show the results, once with and once without controls. Both, levels and three-year changes in profitability predict a credit expansion over the next years. Increasing profitability is associated with subsequent credit expansion.

Table 5: *Multivariate models for changes in credit-to-GDP, disentangling net worth and expectations channels*

	Dependent variable: $\Delta_3 y_{it+3}$					
	Uses of profits				Profit path	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 DoE_{it-1}$	0.95^{***}	0.76^{***}	0.81^{***}	0.70^{***}		
	(0.16)	(0.20)	(0.17)	(0.19)		
$\Delta_3 REToE_{it-1}$			0.27^{***}	0.21^{***}		
			(0.08)	(0.07)		
$RoE_{i,t-1}$					0.44^{***}	0.41^{***}
					(0.09)	(0.10)
$\Delta_3 RoE_{i,t-1}$					0.12^{**}	0.10^{**}
					(0.06)	(0.04)
R^2	0.029	0.121	0.052	0.133	0.092	0.155
Country fixed effects	✓	✓	✓	✓	✓	✓
Distributed lag in Δy		✓		✓		✓
Control variables		✓		✓		✓
Observations	939	939	939	939	1640	1462

Notes: This table reports regressions of credit-to-GDP changes from t to $t+3$ on levels and three-year changes in banking sector profitability measures. Columns (1) to (4) focus on the uses of profits and decompose $\Delta_3 RoE_{i,t-1}$ into dividends over equity ($\Delta_3 DoE_{i,t-1}$) and retained earnings over equity ($\Delta_3 REToE_{i,t-1}$). Columns (5) and (6) study the profit path and include both, the level of profits ($RoE_{i,t-1}$) and the change ($\Delta_3 RoE_{i,t-1}$) in the same regression. Columns (2), (4) and (6) control for three lags of credit-to-GDP changes and a vector of net-worth and macroeconomic control variables (see text in section 3). All specifications include country fixed effects. Standard errors in parentheses are dually clustered on country and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

4.3. Decomposing profitability

As a final step towards disentangling different channels in the long run panel data, we re-estimate the profit-credit relationship for three major constituents of bank profits: revenue, operating costs and loan losses. This decomposition will help us to gain further insights into the mechanisms underlying the profit-credit cycle. As explained above, we were able to locate data that allows us to decompose bank profitability into these categories only for a subset of our sample. Hence, the sample size is reduced relative to the baseline results.

We define three new variables, expressing each of the separate profit components relative to equity to maintain comparability to the baseline estimates. We then run regressions of the following form

$$\Delta_3 y_{i,t+3} = \alpha_i + \beta \Delta_3 (Revenue/Equity)_{i,t-1} + \eta X_{i,t-1} + u_{i,t+3}\,, \tag{8}$$

Table 6: *Multivariate models for changes in credit-to-GDP, profit components*

	Dependent variable: $\Delta_3 y_{it+3}$					
	(1) $\frac{Revenue}{Equity}$	(2) $\frac{Revenue}{Equity}$	(3) $\frac{Cost}{Equity}$	(4) $\frac{Cost}{Equity}$	(5) $\frac{LoanLoss}{Equity}$	(6) $\frac{LoanLoss}{Equity}$
$\Delta_3 Change_{i,t-1}$	0.01		-0.09		-0.25***	
	(0.04)		(0.08)		(0.08)	
$Level_{i,t-1}$		0.03		-0.03		-0.47***
		(0.04)		(0.05)		(0.10)
Country fixed effects	✓	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓	✓
Control variables	✓	✓	✓	✓	✓	✓
R^2	0.14	0.14	0.15	0.14	0.16	0.19
Observations	793	793	793	793	793	793

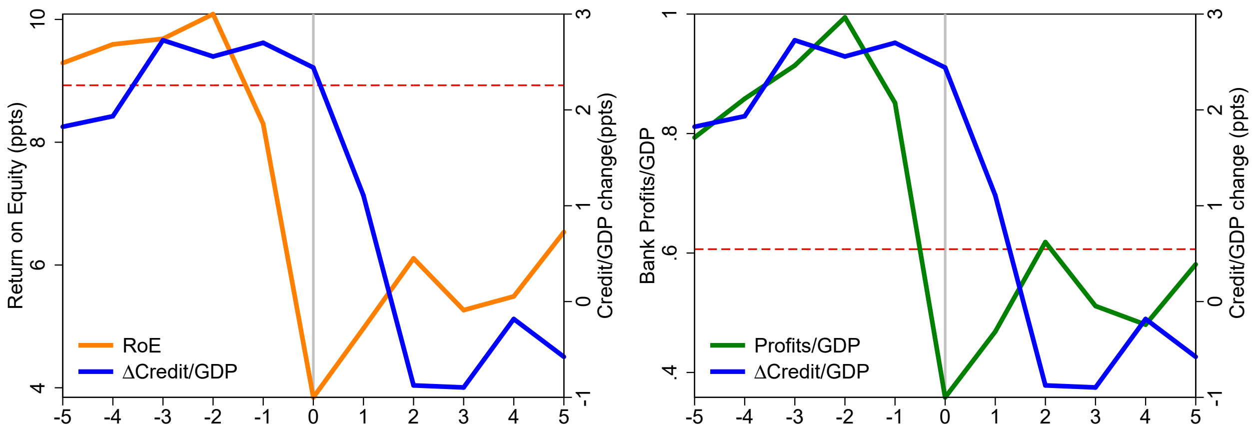
Notes: This table reports regressions of credit-to-GDP changes from t to $t+3$ on levels and three-year changes in banking sector revenue (net interest + net fee income), costs (administrative expenses) and loan losses. All specifications control for three lags of credit-to-GDP changes and a vector of net-worth and macroeconomic control variables (see text in section 3). All specifications include country fixed effects. Standard errors in parentheses are dually clustered on country and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

where we replace $\Delta_3(Revenue/Equity)_{i,t-1}$ with costs and loan losses in alternative specifications. The signs of all coefficients are as we would have expected. Revenues are positively related to credit expansion and costs as well as loan losses negatively. However, revenues and costs are insignificant, while the results for loan losses are highly significant. A decrease in loan losses, or a low level of loan losses, are associated with subsequent credit expansion. In Bordalo et al. (2018b) agents' expectations overweight states of the world that have become more likely in the light of new data. Applied to our setting, news about low or decreasing loan losses lead to an inflated probability of states with low defaults. These low expected losses then enter the lending decisions of banks and create an incentive to extend lending. At the same time, it seems less likely that competition or monetary policy are behind our main result, because these channels would most likely show up through the revenue item. In a similar way, higher efficiency in the banking sector would most likely show up in the cost item. In the data, however, it is loan losses that play the predominant role.

5. Profitability and reversals

Measures of credit expansion are a strong indicator of financial instability risk and usually followed by macroeconomic underperformance (Mian et al., 2017a; Schularick and Taylor,

Figure 4: *Event study of profitability and credit variables around financial crisis dates*



Notes: These figures display the evolution of credit and profit variables around a financial crisis, i.e. 0 refers to a year in which a financial crisis starts. Blue (solid) lines display the mean of changes credit/GDP around crises. The orange line displays *RoE* around crises, the green line the ratio of bank profits to GDP. Red (dashed) lines present the full sample average for the respective variable. All variables are expressed in percentage points.

2012). Our results show that bank profitability tends to lead credit expansions, but does bank profitability also help to understand the transition from boom to crisis? To study this question, the following section focuses on the run-up to financial crisis events. We rely on the narrative chronology by Jordà et al. (2017b) to identify financial crises events.

As a first pass, Figure 4 displays the mean evolution of credit and profit variables in the years around financial crises with year 0 indicating the start of a financial crisis. Blue lines correspond to the yearly change in the ratio of credit to GDP. Credit-to-GDP increases by about 2% in the years prior to financial crisis events and the ratio starts declining two years after a crisis. In addition to credit, the left panel displays in orange the mean level of *RoE* around financial crisis observations, while the red dashed line corresponds to the sample mean of RoE. The graph shows that banking sector profitability is high (above the sample mean) and rising until two years before the crisis. In the year prior to a crisis, there is a reversal and *RoE* already falls below the sample mean. We will study this relationship in more detail below. In line with our previous analysis, visual inspection suggests that the orange curve leads the blue one. Profits predict measures of subsequent credit expansion also around crisis events. The right panel in Figure 4 presents the ratio of bank profits to GDP. While *RoE* is a measure of profit per unit, the latter accounts additionally for changes in the quantity of intermediation and hence for the balance sheet expansion we observe prior to financial crises. Profits relative to GDP display a similar pattern as *RoE* and are significantly elevated with a peak two years prior to a crisis. These patterns can be observed in pre- and post-WW2 data (see Figure A2.2 and Figure A2.3).

5.1. Crisis prediction

We will now explore these relationships econometrically using prediction models that relate bank profitability to the likelihood of experiencing a financial crisis. Specifically, we estimate a probit model for a financial crisis starting in country i in year t, denoted by the binary variable $S_{i,t}$, and assume that the probability of a crisis conditional on observables $X_{i,t-1}$ can be represented in terms of the standard normal cumulative distribution function

$$Pr[S_{i,t} = 1 | \alpha_i, X_{i,t-1}] = \Phi(\alpha_i + \boldsymbol{\beta} X_{i,t-1}) \,, \tag{9}$$

Here $X_{i,t-1}$ is a vector containing lagged measures of profitability and 5-year changes in credit to GDP to control for the well-known relationship between credit and financial crises (Schularick and Taylor, 2012). β denotes the vector of coefficients of interest for the various specifications. We report marginal effects for the relationship between changes in profitability measures and crisis likelihood. We follow the literature and include country fixed effects to account for cross-country heterogeneity in the risk of experiencing a financial crisis.

Column (1) of Table 7 shows a specification where we include the five-year change in RoE, that is the change between $t-6$ and $t-1$. Medium term changes in other variables (notably credit) have been shown to be a good predictor of crisis likelihood and Hamilton (2018) argues that looking at 5-year changes can be a good way to capture cyclical variation in long-run datasets. The coefficient in column (1) is positive, but insignificant. This result changes once we account for the reversal in profitability that can be seen in the event study graphs. When we split the five-year change into a four-year change until $t-2$ and a yearly change in the last year prior to the crisis, we observe that a sequence of increases in profitability predicts higher financial crisis risk further down the road. The one-period lagged change in RoE however enters with a negative sign. Drops in profitability are associated with elevated crisis risk in the following year. Taken together, crisis episodes occur when negative news follow a sequence of positive news. A similar pattern emerges when we look at changes in loan losses. Loan losses decrease between six and two years before a crisis. The sign of the coefficient reverses in the year prior to the crisis, but the result remains insignificant. Finally, we study the behavior of bank profits to GDP, accounting for increases in the quantity of intermediated funds, in columns (5) and (6). The pattern is the same as for RoE: profits increase until two years before a crisis and there is a significant reversal one-year ahead of the crisis. In Table A2.11 we present the results when we split the profitability changes into five yearly lags.

Table 7: *Multivariate probit models for systemic financial crisis*

	RoE		Loan Losses/Loans		Profits/GDP	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_{t-6\to t-1}$	0.05		-0.89		0.83*	
	(0.06)		(0.82)		(0.43)	
$\Delta_{t-2\to t-1}$		-0.07**		0.21		-0.91**
		(0.03)		(0.75)		(0.40)
$\Delta_{t-6\to t-2}$		0.24***		-1.68**		1.71***
		(0.07)		(0.70)		(0.42)
Credit Growth	✓	✓	✓	✓	✓	✓
AUROC	0.72	0.75	0.72	0.73	0.72	0.76
Number of Crises	55	55	40	40	55	55
Observations	1634	1634	909	909	1622	1622

Notes: The table shows probit classification models where the dependent variable is a financial crisis dummy. Columns (1), (3) and (5) include the lagged 5-year change in *RoE*, Loan losses/Loans and Profits/GDP. In columns (2), (4) and (6) these changes are split into the 4-year change between $t-6$ and $t-2$ and the change between $t-2$ and $t-1$. All models include country fixed effects and the 5-year change in the ratio of credit to GDP. Coefficients are marginal effects. Country clustered standard errors in parentheses. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

We have shown before that increases in profitability are associated with subsequent credit expansions. The credit booms that eventually end in financial crises are no exception and are preceded by increases in profitability. The evolution of profitability around crisis events furthermore shares some of the key characteristics of behavioral credit cycle models (Bordalo et al., 2018b): the crisis occurs following negative news after a series of good fundamental news. Low loan losses in the periods prior to the crisis are consistent with the "calm before the storm" period in (Greenwood et al., 2018). The findings also mirror previous evidence in the empirical macro-finance literature. Krishnamurthy and Muir (2017) argue that credit spreads are too low prior to financial crises and Danielsson et al. (2018) show that equity volatility is low. We find similar evidence in measures of bank profitability, and the cycle turns when profitability starts to fall.

5.2. Return predictability

Increases in profitability predict crisis risk. Using data on total bank equity index excess returns, we can also mirror the analysis of Baron and Xiong (2017) and ask whether bank shareholders are compensated for elevated downside risks when profitability is increasing. Shareholders who are aware of increased crisis likelihood would require higher expected returns to be compensated for holding bank stocks during a high risk period. Whether this

Table 8: *Predictive regression for bank equity index excess returns*

	Dependent variable: cumulative bank equity index excess returns					
	(1) 1-year	(2) 2-year	(3) 3-year	(4) 4-year	(5) 5-year	(6) 6-year
$\Delta_3 RoE_{i,t-1}$	-0.01	-0.01	-0.05*	-0.08**	-0.08*	-0.06**
	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)
$\Delta_3 Loans/GDP_{i,t-1}$	-0.05***	-0.08***	-0.11***	-0.11**	-0.11***	-0.09**
	(0.01)	(0.02)	(0.03)	(0.04)	(0.04)	(0.03)
Country fixed effects	✓	✓	✓	✓	✓	✓
Observations	899	867	839	813	787	764

Notes: This table reports estimates for a panel regression of bank equity index excess returns on lagged three-year changes in return on equity ($\Delta_3 RoE_{i,t-1}$) and lagged three-year changes of the credit to GDP ratio ($\Delta_3 Loans/GDP_{i,t-1}$). Both explanatory variables are standardized on the country level. The dependent variable is log excess total returns cumulated over h years, where h is specified in the column header. All specifications include country fixed effects. Standard errors in parentheses are computed using the Driscoll and Kraay (1998) method accounting for autocorrelation of up to $2 \times h$ lags. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

is the case can be analysed with a predictive regression of cumulative excess returns (h years ahead) of the bank equity index on measures of past profitability

$$r_{i,t+h} - r^{f}_{i,t+h} = \alpha_{h,i} + \beta^{h}_{1} \Delta_3 RoE_{i,t-1} + \beta^{h}_{2} \Delta_3 Credit/GDP_{i,t-1} + \epsilon_{i,t+h}, \tag{10}$$

for $h = 1,...,6$. Motivated by the idea that increases in profitability mark the beginning of a credit expansion that is followed by a reversal a few years later, we extend the horizon compared to Baron and Xiong (2017) and look at horizons of up to six years. We furthermore lag the explanatory variable by one year to stay consistent with our previous analysis and avoid a mechanical relationship between profits and returns. The results are presented in Table 8, where we include in addition to the three-year change in return on equity the credit-to-GDP change. To account for cross-country differences in the variance of profitability and credit expansions, we standardize our predictor variables at the country level.

The results for the three-year credit expansion variable are close to the estimates in Baron and Xiong (2017) at horizons up to three years. Three year changes in RoE forecasts negative but barely significant excess returns over the first three years. However, consistent with the idea that elevated profits first trigger a period of overoptimism that is a few years later followed by a predictable reversal, we find that profitability forecasts significantly lower excess returns over horizons between four and six years. Bank shareholders are systematically disappointed a few years after an increase in profitability. Put differently, following an increase in profitability, investors seem to be excessively optimistic about future prospects in the banking sector.

6. Survey expectations and credit expansions

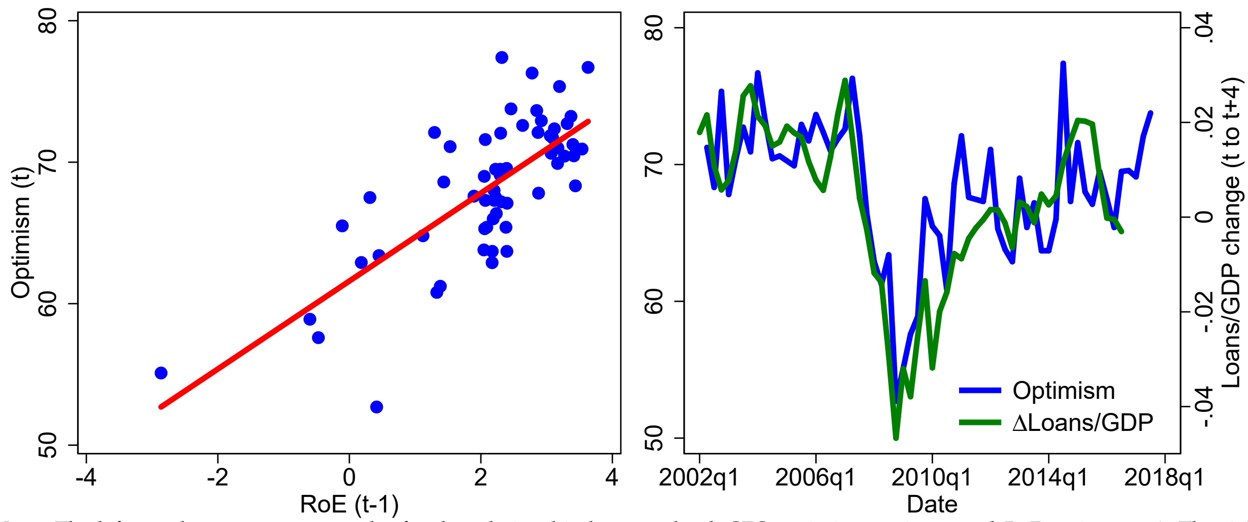
Profitability in the banking sector predicts credit expansion and it is linked to reversals. These reversals could be interpreted as moments of sudden changes in expectations. We now explore the link between bank profitability and direct, survey-based measures of expectations. Survey-based information about bankers' expectations is scarce. We therefore turn to recent data from the United States. Based on responses of bank CFOs (from the Duke CFO Global Business Outlook, 2018), we ask whether optimism and expectations about future profitability are related to recent changes in profitability and how they affect subsequent changes in bank credit.

The Duke CFO Global Business Outlook (2018) asks respondents to rate their optimism about the financial prospects of their own company on a scale from 0-100, with 0 being the least optimistic and 100 being the most optimistic. CFOs are further asked about their expectations of changes in earnings over the next twelve months. For both questions, we have quarterly data on the mean response of CFOs from the banking and finance industry (starting in 2002 and 1998 respectively). We combine these measures with quarterly accounting information on realized profitability and credit growth.[4] We first confirm that the baseline relationships between profitability measures and subsequent credit growth in this sample mirror the correlations in the long-run cross-country data (see Figure A3.4 in the appendix).

As a first cut of the data, the left panel of Figure 5 shows a scatterplot for the relationship between the optimism measure and lagged *RoE*, where *RoE* is defined as *Net Operating Income/Total Equity Capital* from the FDIC statistics. Clearly, lagged *RoE* is positively associated with optimism. The higher past profitability, the more optimistic are bank CFOs. Furthermore, the right panel shows that optimism at time t and changes in the credit/GDP ratio between t and $t+4$ track each other closely. The banking sector extends more credit over the following year, when CFO optimism is elevated today.

[4] Quarterly balance sheet and income information are based on FDIC statistics. We use aggregated data from quarterly banking profile spreadsheets, in particular "Assets and Liabilities of FDIC-Insured Commercial Banks and Savings Institutions" and "Quarterly Income and Expense of FDIC-Insured Commercial Banks and Savings Institutions". The data can be accessed here https://www.fdic.gov/bank/analytical/qbp/.

Figure 5: *Profitability, optimism and credit growth*



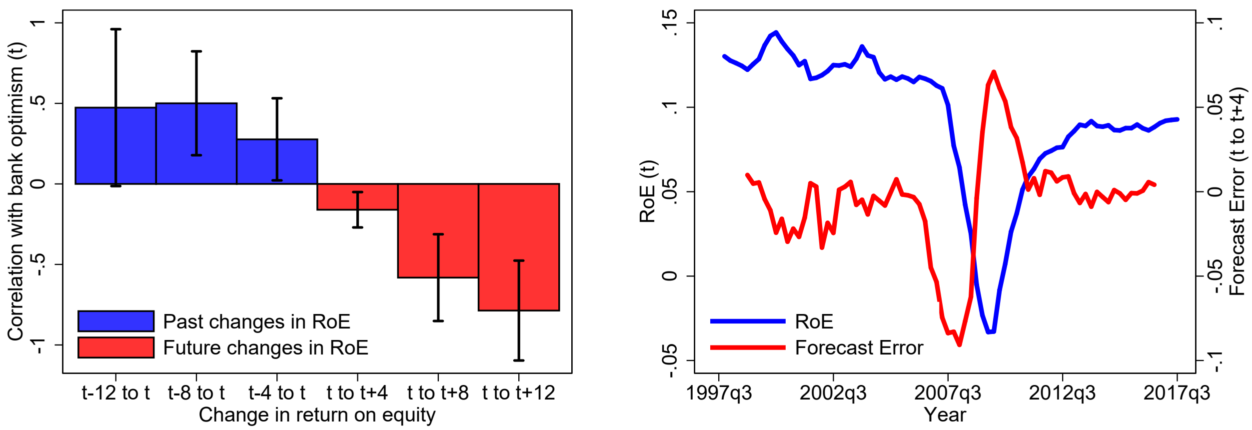
Notes: The left panel presents a scatterplot for the relationship between bank CFO optimism at time t and RoE at time $t-1$. The right panel presents the evolution of bank CFO optimism and subsequent 4-quarter changes in the ratio of net loans and leases to GDP (between t and $t+4$).

Optimism is an appealing measure for credit market sentiment, but it is important to note that optimism could be justified by subsequent developments in profitability. We therefore study the correlation structure between optimism and past and future changes in profitability. The left-hand panel of Figure 6 shows the correlation of CFO optimism at time t with cumulative changes in profitability over the previous and following three years. We find that bank CFOs become optimistic about the future when profits were increasing in the years prior to time t. However, the optimistic outlook into the future is not ex-post validated by further profit increases. In fact, high optimism predicts decreasing profits over the next 3 years. For a more formal test we rely on the survey responses about expected changes in earnings to compare realized and expected profitability. We first calculate the time t expectation of RoE_{t+4} multiplying actual earnings over the past twelve months at time t with expected earnings changes over the next twelve months (from the CFO survey) scaled with time t equity capital.

$$E_t[RoE_{t+4}] = \frac{ExpectedChange_{t\rightarrow t+4} \times \sum_{i=0}^{3} NetOperatingIncome_{t-i}}{EquityCapital_t} \tag{11}$$

$E_t[RoE_{t+4}]$ can be compared to realized RoE_{t+4}, computed as realized earnings over the following twelve months, also scaled with time t equity capital. We refer to the difference between the two as the time t forecast error ($Error_t = RoE_{t+4} - E_t[RoE_{t+4}]$). The time series for this variable is visualized in the left-hand panel of Figure 6 together with realized

Figure 6: *Current profitability and forecast errors*



Notes: The left-hand panel reports regression coefficients of changes in return on equity from $t-h$ to t and from t to $t+h$ on bank CFO optimism at t for $h = 4, 8, 12$. Error bars indicate 90% confidence intervals. Newey-West standard errors computed using the automatic bandwidth selection procedure in Newey and West (1994). The right-hand panel displays the evolution of bank RoE_t and time t return on equity forecast errors ($RoE_{t+4} - E_t[RoE_{t+4}]$) of bank CFOs in the United States between 1997 and 2017. See text.

profitability over the past twelve months. The negative relationship between the two measures suggests that CFOs are too optimistic (expected profitability is higher than realized profitability) when current RoE is high and vice versa.

Table 9 presents empirical tests of these relationships. In column (1), we find a positively significant relationship between changes in optimism and changes in RoE. An increase in profitability is associated with a more optimistic outlook of the average CFO on the future financial prospects of the bank. Column (2) shows that this optimism is not justified in the data. There is in fact no association between changes in RoE today and the change over the next year. At the same time, in line with the optimism measure, expectations of profitability over the following year are elevated if RoE increases (column (3)). As a result, expectations are systematically biased. The difference between realized and expected earnings, the forecast error, is negatively related with changes in RoE. Put differently, an increase in RoE is associated with an increase in expected profitability relative to realized profitability over the following year. In column (5), we study the implications for credit supply conditions. The dependent variable here is the change in the net percentage of banks tightening standards for loans to large and middle-market firms from the Federal Reserve's senior loan officer opinion survey. The negative coefficient implies that a significant fraction of banks loosens credit standards when RoE increases.

In a second step we link these variables to the credit cycle. We measure credit growth as the change in the ratio of net loans and leases to GDP between t and $t+4$. Column (1)

Table 9: *Relationship between profitability, expectations about future profitability and credit supply conditions*

	$\Delta Optimism$	ΔRoE_{t+4}	$\Delta E_t(RoE_{t+4})$	$\Delta Error$	$\Delta\%Tightening$
	(1)	(2)	(3)	(4)	(5)
ΔRoE_t	1.70***	0.06	0.73***	-0.66***	-7.14***
	(0.52)	(0.14)	(0.19)	(0.23)	(0.99)
R^2	0.08	0.00	0.17	0.10	0.18
Observations	57	78	73	69	82

Notes: This table reports estimates for univariate regressions of the change in return on equity on bank expectations, future profitability and profit forecast errors. In column (1), the dependent variable is the change in optimism from the bank CFO survey, in column (2) the change in realized earnings between t and t+4 normalized with equity capital at time t, in column (3) the change in expected earnings between t and t+4 normalized with equity capital at time t, in column (4) the change in the difference between realized and expected earnings between t and t+4, in column (5) the change in the net percentage of domestic banks tightening standards for C&I loans to large and middle-market firms. Newey-West standard errors in parentheses are computed using the automatic bandwidth selection procedure in Newey and West (1994). *, **, ***: Significant at 10%, 5% and 1% levels respectively.

in Table 10 confirms that 4-quarter changes in credit are predicted by optimism, where lagged credit growth, a crisis and a recession dummy, as well as GDP growth, interest rates and bank capital ratios are included as control variables. In column (2) we include realized profitability over the past year. This is now a narrower time frame than in our main exercises, but remember, we confirmed before that the relationship between profitability and three year changes in credit/GDP also holds in this recent sample. Columns (3) and (4) analyze the relationship between profit forecasts and credit growth. The profit forecast itself (column (3)) is positively related to subsequent credit growth. When expected profits are high, credit grows rapidly. The forecast error is negatively related to credit growth: credit growth is low when bank CFOs are excessively pessimistic and it is high when they are excessively optimistic. Finally, column (5) illuminates one possible channel and shows that a tightening (loosening) in the standards at which banks supply credit is associated with lower (higher) credit growth over the following years.

Overall, the findings are consistent with the idea that bankers' expectations rely excessively on recent performance. Furthermore, survey-based measures of expectations are linked to credit growth, and expectational errors are reflected in the growth rate of credit.

7. Bank level evidence

If banks (loan officers) indeed form expectations based on recent credit outcomes, we would expect to find evidence for the profit-credit cycle also at the bank level. Credit outcomes

Table 10: *Multivariate models for changes in credit-to-GDP, profitability and expectations*

	Dependent variable: 4-quarter change in credit/GDP				
	(1)	(2)	(3)	(4)	(5)
	$Optimism$	RoE_t	$E_t(RoE_{t+4})$	$Error$	$\%Tightening$
RHS variable (see column header)	0.13***	0.37***	0.29***	-0.28***	-0.02***
	(0.04)	(0.04)	(0.03)	(0.05)	(0.01)
R^2	0.79	0.85	0.83	0.71	0.65
Controls	✓	✓	✓	✓	✓
Observations	56	75	71	71	75

Notes: This table reports regressions of bank earnings and expectation measures on changes in credit to GDP ratios. The dependent variable is the change in the ratio of net loans and leases to annualized quarterly GDP between t and t+4. In column (1) this change is regressed on optimism from the bank CFO survey, in column (2) on realized earnings between t-4 and t normalized with equity capital at time t, in column (3) expected earnings between t and t+4 normalized with equity capital at time t, in column (4) the change in the difference between realized and expected earnings between time t and t+4 normalized with equity capital at time t, in column (5) the net percentage of domestic banks tightening standards for C&I loans to large and middle-market firms. Newey-West standard errors in parentheses are computed using the automatic bandwidth selection procedure in Newey and West (1994). *, **, ***: Significant at 10%, 5% and 1% levels respectively.

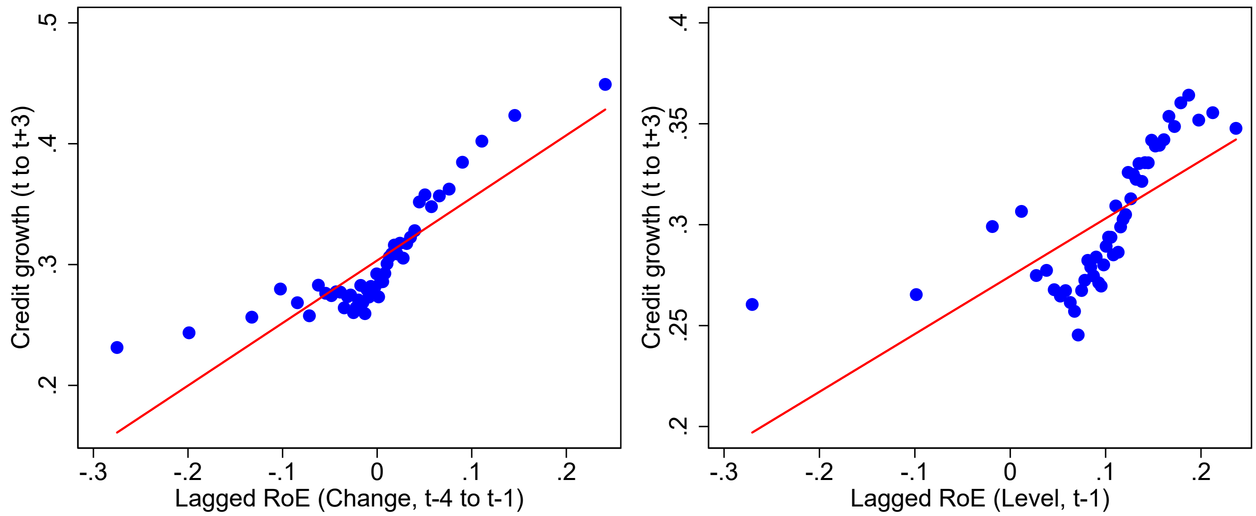
experienced by a bank should have a strong impact on bankers' expectations and thereby predict bank-level credit growth.

To study this prediction, we employ bank call report data provided by the Federal Reserve. Banks are required to file these reports for regulatory purposes and the data contain detailed quarterly income and balance sheet statements for all US commercial banks. We use data between 1983 and 2012, when all balance sheet and income statement items for our analysis are available in the same format. We first transform quarterly call report data into annual observations, by summing income items over the four quarters of a given year. We then combine yearly income with end-of-year balance sheet values. We exclude bank-year observations with assets or loans being less than one million USD, or with negative equity, and we winsorize all variables at the 2.5% level.

The resulting panel dataset with bank-year observations allows us to run specifications mirroring closely the empirical exercises in the aggregate setting. Now, the dependent variable is defined as the change in *net loans and leases* of bank i between year t and year $t+3$. $RoE_{i,t}$ is defined as yearly net income scaled by end-of-year equity. As before, we also compute the three-year change in this variable $\Delta_3 RoE_{i,t} = RoE_{i,t} - RoE_{i,t-3}$.

Figure 7 shows scatterplots with the data collapsed into fifty bins, depending on profitability measures. There is a strong positive correlation between lagged changes in profitability ($\Delta_3 RoE_{i,t-1}$) and subsequent credit growth in the left panel and lagged levels of profits

Figure 7: *Binned scatterplot for the relationship between profitability and credit growth, bank level data*



Notes: The figure relates bank profitability and subsequent credit growth on a bank level. Bank level observations are collapsed into 50 equal sized bins according to the two profitability measures. Each point represents group specific profitability and credit growth means for our regression sample. Fitted regression lines illustrate the correlation between bank profitability and subsequent credit growth.

($RoE_{i,t-1}$) and subsequent three-year credit growth in the right panel. In order to test this relationship more formally, we run the following regression:

$$\Delta_3 y_{i,t+3} = \alpha_i + \alpha_t + \beta \Delta_3 RoE_{i,t-1} + \gamma X_{i,t-1} + u_{i,t+3}. \tag{12}$$

Crucially, in this regression α_t is a year fixed effect, controlling for aggregate credit demand conditions at time t. α_i is a bank fixed effect that controls for bank specific time-invariant characteristics. β will be the coefficient of interest that refers to either the lagged level of RoE or to the lagged three-year change in profitability. Control variables $X_{i,t-1}$ are now at the bank level. Here we include past credit growth, and in addition lagged balance sheet shares of equity, loans, deposits, fed funds (liabilities) and bank size (natural log of assets). Three-year changes in capital proxy for the net worth channel. The advantage in this setup is that we can control for net-worth at the bank level and therefore rule out balance sheet constraints more directly, accounting for the possibility that the distribution of net worth across banks matters.

The results are shown in Table 11. In column (1) we see that credit growth over the following 3-year window is higher when profitability has been increasing. The coefficient is positive and highly significant. In line with a net-worth channel, three-year changes in equity capital are associated with stronger loan growth over the following periods ($\Delta_3 Capital_{i,t-1}$). Column (2) replaces lagged three-year changes of profitability with lagged

Table 11: *Multivariate models for credit growth, bank level data*

	Dependent variable: $\Delta_3 y_{it+3}$					
	(1) Full	(2) Full	(3) Full	(4) No-overlap	(5) No-overlap	(6) No-overlap
$\Delta_3 RoE_{it-1}$	0.12^{***}		0.11^{***}	0.17^{***}		0.12^{***}
	(0.02)		(0.03)	(0.05)		(0.04)
RoE_{it-1}		0.12^{***}	0.03		0.20^{**}	0.10
		(0.04)	(0.05)		(0.08)	(0.09)
$Capital\ Ratio_{it-1}$	-0.34^{**}	-0.36^{**}	-0.34^{**}	-0.28	-0.30	-0.28
	(0.15)	(0.15)	(0.15)	(0.19)	(0.21)	(0.20)
$\Delta_3 Capital_{it-1}$	0.04^{***}	0.04^{***}	0.04^{***}	0.04^{***}	0.04^{**}	0.04^{**}
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Bank fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓
Control variables	✓	✓	✓	✓	✓	✓
R^2	0.20	0.20	0.20	0.21	0.21	0.21
Observations	178605	178605	178605	56122	56122	56122

Notes: This table reports regression results from estimating variants of Equation 12 using US Call Report data. The dependent variable $\Delta_3 y_{it+3}$ is the three year change of bank credit (net loans and leases). All variables are winsorized at the 2.5% level. Columns (1), (2) and (3) report results for all years. Column (4), (5) and (6) restrict the data to non-overlapping observations only. All specifications control for the lagged three-year growth rate of net loans and leases, relevant balance sheet ratios, bank size and bank net-worth (see text). All specifications also include bank and year fixed effects. Standard errors in parentheses are dually clustered on bank and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

levels in RoE and we obtain similar results. Column (3) includes levels and changes of profitability. As argued before, controlling for the level of RoE, three-year changes proxy for the trajectory that led a bank to a certain level of profitability. The latter should play a role under extrapolative expectations, but not affect the net worth channel. In line with the expectations channel, changes in RoE are significantly related to subsequent credit growth. In columns (4) to (6) we repeat the procedure for non-overlapping windows of observations. This reduces the number of observations to a third, but the results remain unaffected. Table A4.13 in the appendix shows qualitatively similar results when we replace profitability with loan losses.

Bank level results are consistent with the aggregate evidence presented previously. Both, lagged profitability and 3-year changes therein are positively related to subsequent 3-year credit growth. Importantly, the results are not affected by the inclusion of time fixed effects. Thus, the channel that links profits and subsequent credit growth is not contingent on or subsumed by an aggregate demand channel for credit.

8. Conclusion

The Minsky (1977)-cycle starts with a positive displacement. Positive news breed optimism, and lead to a boom in credit markets, but also to elevated crisis risk down the road. In this paper, we set out to study the boom, to make sense of the bust.

We establish a new robust fact: bank profitability leads the credit cycle. Credit expands following increases in profitability. Decomposing profitability, we find that loan losses play an important role for the relationship between profits and credit aggregates. Our results are consistent with a recent theoretical literature on the role of expectational biases in shaping the credit cycle. When loan losses are low, economic agents seem to extrapolate these conditions into the future, increasing aggregate leverage in the economy. Similarly, when loan losses are high, banks become more pessimistic and the availability of credit is reduced. We show that reported expectations of bank CFOs from survey data are consistent with such a channel.

The relationship between profits and credit also helps to understand the transition from boom to bust. Measures of bank profits spike two years before a crisis. The reversal in profits and loan losses marks the turning point of the credit cycle and is often followed by a banking crisis with severe credit contractions.

Is there anything special about credit as an instrument and banks as intermediaries? Simsek (2013) shows that overoptimism of lenders about downside states matters in particular. A similar reasoning leads us to believe that the biases at the bank level may be more important than at the borrower level. If corporate managers extrapolate and become excessively optimistic, but bankers rationally anticipate risks, risk would be priced. This reasoning is also mirrored in recent theoretical contributions stressing the importance of biased expectations of lenders for credit dynamics (Bordalo et al., 2019; Kaplan et al., 2017). Taken together, the evidence presented in this paper suggests that return extrapolation at the bank level can have important macroeconomic consequences through its effects on credit supply and financial stability risks in the economy.

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Appendix

A. Additional results

A1. Robustness: main results

Table A1.1: *Alternative dependent variable – real private credit per capita*

	Dependent variable: $\Delta_3 y_{it+3}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 RoE_{i,t-1}$	0.57***	0.45***	0.45***			
	(0.18)	(0.12)	(0.12)			
$RoE_{i,t-1}$				0.79***	0.63***	0.67***
				(0.20)	(0.14)	(0.15)
$Capital\ Ratio_{i,t-1}$			-0.02			-0.03
			(0.34)			(0.34)
$\Delta_3(Capital/GDP)_{i,t-1}$			-0.86			-1.18
			(0.85)			(0.86)
Country fixed effects	✓	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓	✓
Macrocontrols		✓	✓		✓	✓
Net-Worth Channel			✓			✓
R^2	0.04	0.12	0.12	0.06	0.13	0.14
Observations	1621	1464	1462	1658	1496	1486

Notes: This table reports regressions of real private credit per capita changes from t to $t+3$ on RoE_{it-1} and $\Delta_3 RoE_{i,t-1}$. All specifications control for three lags of real private credit per capita. Columns (2) and (5) add a vector of macroeconomic control variables (see text in section 3). Columns (3) and (6) additionally control for net-worth channel proxies. All specifications include country fixed effects. Standard errors in parentheses are dually clustered on country and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

Table A1.2: *Alternative dependent variable – bank assets/GDP*

	Dependent variable: $\Delta_3 y_{it+3}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 RoE_{i,t-1}$	0.47^{**}	0.54^{**}	0.56^{***}			
	(0.23)	(0.21)	(0.20)			
$RoE_{i,t-1}$				0.84^{***}	0.95^{***}	0.92^{***}
				(0.23)	(0.25)	(0.24)
$Capital\ Ratio_{i,t-1}$			0.30			0.30
			(0.22)			(0.22)
$\Delta_3(Capital/GDP)_{i,t-1}$			1.48			1.07
			(1.37)			(1.38)
Country fixed effects	✓	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓	✓
Macrocontrols		✓	✓		✓	✓
Net-Worth Channel			✓			✓
R^2	0.03	0.10	0.10	0.06	0.12	0.13
Observations	1628	1477	1477	1658	1504	1503

Notes: This table reports regressions of bank assets/GDP changes from t to $t+3$ on RoE_{it-1} and $\Delta_3 RoE_{i,t-1}$. All specifications control for three lags of bank assets-to-GDP. Columns (2) and (5) add a vector of macroeconomic control variables (see text in section 3). Columns (3) and (6) additionally control for net-worth channel proxies. All specifications include country fixed effects. Standard errors in parentheses are dually clustered on country and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

Table A1.3: *Alternative dependent variable – non-loan bank assets/GDP*

	Dependent variable: $\Delta_3 y_{it+3}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 RoE_{i,t-1}$	0.13	0.27	0.29			
	(0.19)	(0.20)	(0.18)			
$RoE_{i,t-1}$				0.35^{*}	0.44^{**}	0.43^{*}
				(0.20)	(0.22)	(0.22)
$Capital\ Ratio_{i,t-1}$			0.04			0.06
			(0.22)			(0.21)
$\Delta_3(Capital/GDP)_{i,t-1}$			0.71			0.43
			(1.02)			(1.07)
Country fixed effects	✓	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓	✓
Macrocontrols		✓	✓		✓	✓
Net-Worth Channel			✓			✓
R^2	0.02	0.09	0.09	0.03	0.09	0.09
Observations	1592	1444	1444	1620	1469	1468

Notes: This table reports regressions of non-loan bank assets/GDP changes from t to $t+3$ on RoE_{it-1} and $\Delta_3 RoE_{i,t-1}$. All specifications control for three lags of non-loan bank assets/GDP. Columns (2) and (5) add a vector of macroeconomic control variables (see text in section 3). Columns (3) and (6) additionally control for net-worth channel proxies. All specifications include country fixed effects. Standard errors in parentheses are dually clustered on country and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

Table A1.4: *Alternative dependent variable – loan-to-deposit ratio*

	Dependent variable: $\Delta_3 y_{it+3}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 RoE_{i,t-1}$	0.35***	0.30***	0.31***			
	(0.11)	(0.07)	(0.07)			
$RoE_{i,t-1}$				0.51***	0.38***	0.39***
				(0.13)	(0.14)	(0.14)
$Capital\ Ratio_{i,t-1}$			-0.22			-0.20
			(0.14)			(0.16)
$\Delta_3(Capital/GDP)_{i,t-1}$			0.10			-0.16
			(0.34)			(0.30)
Country fixed effects	✓	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓	✓
Macrocontrols		✓	✓		✓	✓
Net-Worth Channel			✓			✓
R^2	0.03	0.10	0.11	0.05	0.11	0.11
Observations	1603	1451	1450	1635	1479	1476

Notes: This table reports regressions of loan/deposit ratio changes from t to $t+3$ on RoE_{it-1} and $\Delta_3 RoE_{i,t-1}$. All specifications control for three lags of the loan/deposit ratio. Columns (2) and (5) add a vector of macroeconomic control variables (see text in section 3). Columns (3) and (6) additionally control for net-worth channel proxies. All specifications include country fixed effects. Standard errors in parentheses are dually clustered on country and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

Table A1.5: *Alternative profitability measure – return on assets*

	Dependent variable: $\Delta_3 y_{it+3}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 RoA_{it-1}$	4.52***	3.89***	3.82***			
	(0.67)	(0.57)	(0.54)			
$RoA_{i,t-1}$				2.68***	4.28***	5.04***
				(0.90)	(0.95)	(1.12)
$Capital\ Ratio_{i,t-1}$			0.23***			-0.16
			(0.09)			(0.13)
$\Delta_3(Capital/GDP)_{i,t-1}$			0.04			0.04
			(0.23)			(0.25)
Country fixed effects	✓	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓	✓
Macrocontrols		✓	✓		✓	✓
Net-Worth Channel			✓			✓
R^2	0.05	0.11	0.12	0.04	0.14	0.14
Observations	1617	1469	1462	1646	1494	1486

Notes: This table reports regressions of credit-to-GDP changes from t to $t+3$ on RoA_{it-1} and $\Delta_3 RoA_{i,t-1}$. All specifications control for three lags of credit-to-GDP changes. Columns (2) and (5) add a vector of macroeconomic control variables (see text in section 3). Columns (3) and (6) additionally control for net-worth channel proxies. All specifications include country fixed effects. Standard errors in parentheses are dually clustered on country and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

Table A1.6: *Alternative profitability measure – log real profits per capita*

	Dependent variable: $\Delta_3 y_{it+3}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 Log(profits)_{i,t-1}$	0.04***	0.04***	0.04***			
	(0.01)	(0.00)	(0.00)			
$Log(profits)_{i,t-1}$				0.01***	0.02***	0.02***
				(0.00)	(0.00)	(0.01)
$Capital\ Ratio_{i,t-1}$			0.21***			0.13
			(0.08)			(0.09)
$\Delta_3(Capital/GDP)_{i,t-1}$			-0.22			-0.12
			(0.28)			(0.30)
Country fixed effects	✓	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓	✓
Macrocontrols		✓	✓		✓	✓
Net-Worth Channel			✓			✓
R^2	0.06	0.11	0.12	0.05	0.10	0.11
Observations	1503	1359	1359	1576	1426	1419

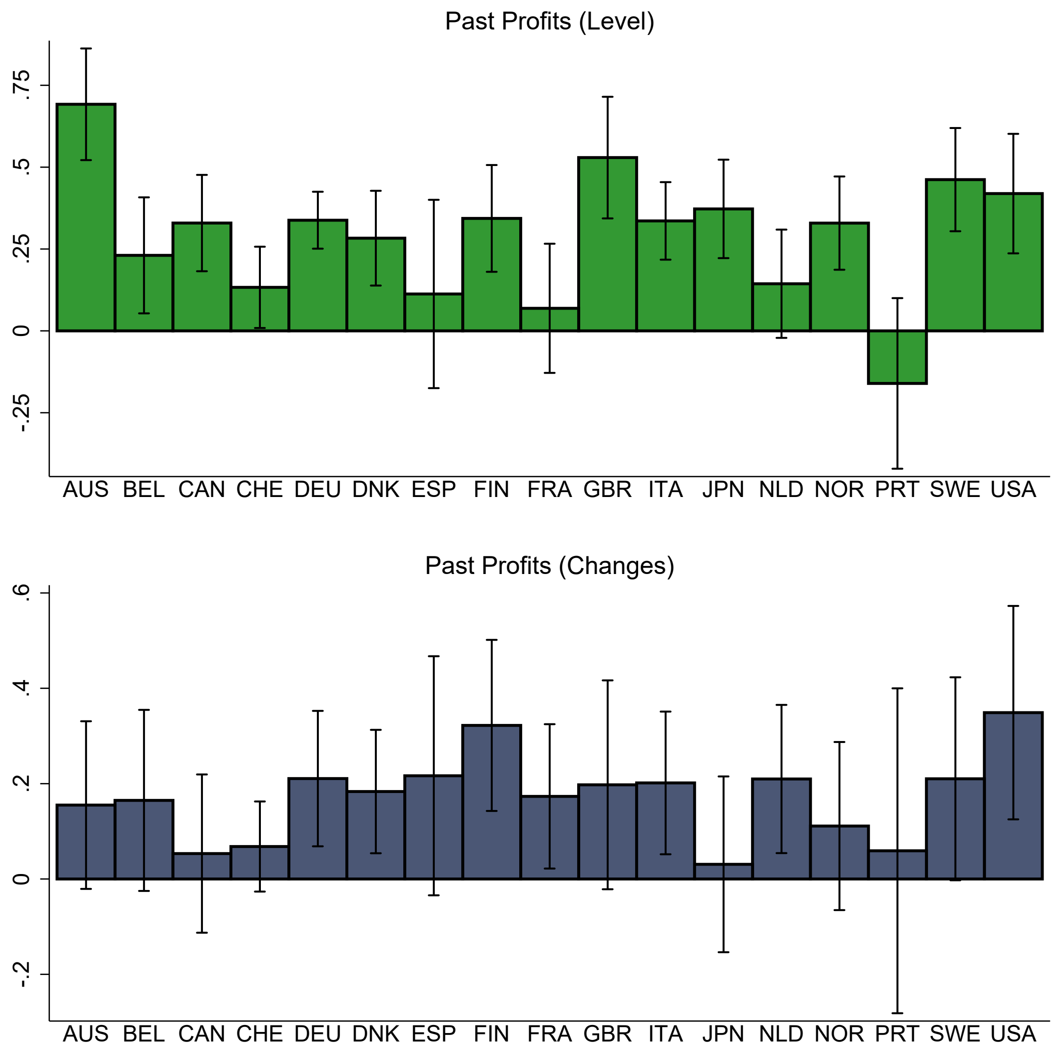
Notes: This table reports regressions of credit-to-GDP changes from t to $t+3$ on $log(profits)_{it-1}$ and $\Delta_3 log(profits)_{i,t-1}$. $Log(profits)$ is the logarithm of real profits per capita. All specifications control for three lags of credit-to-GDP changes. Columns (2) and (5) add a vector of macroeconomic control variables (see text in section 3). Columns (3) and (6) additionally control for net-worth channel proxies. All specifications include country fixed effects. Standard errors in parentheses are dually clustered on country and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

Table A1.7: *Alternative profitability measure – profits/GDP*

	Dependent variable: $\Delta_3 y_{it+3}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 Profits\ to\ GDP_{i,t-1}$	6.02***	5.39***	5.24***			
	(0.73)	(0.55)	(0.55)			
$Profits\ to\ GDP_{i,t-1}$				4.94***	4.67***	4.62***
				(1.12)	(0.94)	(0.93)
$Capital\ Ratio_{i,t-1}$			0.21**			0.05
			(0.09)			(0.11)
$\Delta_3(Capital/GDP)_{i,t-1}$			-0.07			-0.16
			(0.24)			(0.24)
Country fixed effects	✓	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓	✓
Macrocontrols		✓	✓		✓	✓
Net-Worth Channel			✓			✓
R^2	0.09	0.14	0.14	0.07	0.14	0.14
Observations	1610	1462	1462	1645	1493	1486

Notes: This table reports regressions of credit-to-GDP changes from t to $t+3$ on $Profits\ to\ GDP_{it-1}$ and $\Delta_3 Profits\ to\ GDP_{i,t-1}$. All specifications control for three lags of credit-to-GDP changes. Columns (2) and (5) add a vector of macroeconomic control variables (see text in section 3). Columns (3) and (6) additionally control for net-worth channel proxies. All specifications include country fixed effects. Standard errors in parentheses are dually clustered on country and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

Figure A1.1: *Country-level regression coefficients*



Notes: This figure reports regression coefficients and 90% confidence intervals from individual country regressions of credit-to-GDP changes from t to $t+3$ on RoE_{it-1} and $\Delta_3 RoE_{i,t-1}$. The specifications are $\Delta_3 y_{t+3} = \alpha + \beta^{RoE} RoE_{t-1} + u_{t+3}$ and $\Delta_3 y_{t+3} = \alpha + \beta^{\Delta RoE} \Delta_3 RoE_{t-1} + u_{t+3}$ estimated on individual country samples. Variables have been standardized by country for comparability of coefficients.

Table A1.8: *Predicting changes in RoE with lagged profitability and bank equity index excess returns*

	(1) ΔRoE_{it}
$RoE_{i,t-1}$	0.01
	(0.15)
$\Delta RoE_{i,t-1}$	-0.39***
	(0.07)
$\Delta RoE_{i,t-2}$	-0.33***
	(0.06)
$\Delta RoE_{i,t-3}$	-0.13***
	(0.03)
Bank equity index excess return$_{it-1}$	0.01
	(0.02)
Bank equity index excess return$_{it-2}$	-0.02
	(0.02)
Bank equity index excess return$_{it-3}$	-0.01
	(0.02)
R^2	0.160
Credit growth	✓
Observations	901

Notes: This table reports regression estimates of changes in return on equity on the lagged return on equity level and three lags of changes in return on equity, excess returns on bank equity, and changes in credit to GDP ratios. Regression specification: $\Delta RoE_{i,t} = \alpha_i + \beta RoE_{i,t-1} + \sum_{h=1}^{3} \gamma_h \Delta RoE_{i,t-h} + \sum_{h=1}^{3} \iota_h Returns_{i,t-h} + \sum_{h=1}^{3} \omega_h \Delta Credit/GDP_{i,t-h} + \epsilon_{i,t}$. Standard errors in parentheses are clustered on the country level. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

Table A1.9: *Credit expansion following surprises in bank profitability*

	(1)	(2)
Residual ΔRoE_{it-1}	0.15***	0.10**
	(0.04)	(0.04)
Country fixed effects	✓	✓
Distributed lag in Δy	✓	✓
Control variables		✓
R^2	0.07	0.14
Observations	785	776

Notes: This table reports estimates of Equation 6 using residuals from a predictive regression as the main explanatory variable. The regression coefficients of the first stage are reported in appendix Table A1.8. All specifications include country fixed effects and three lags of credit-to-GDP changes. Column (2) adds a vector of net-worth and macroeconomic control variables (see text in section 3). Standard errors in parentheses are dually clustered on country and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

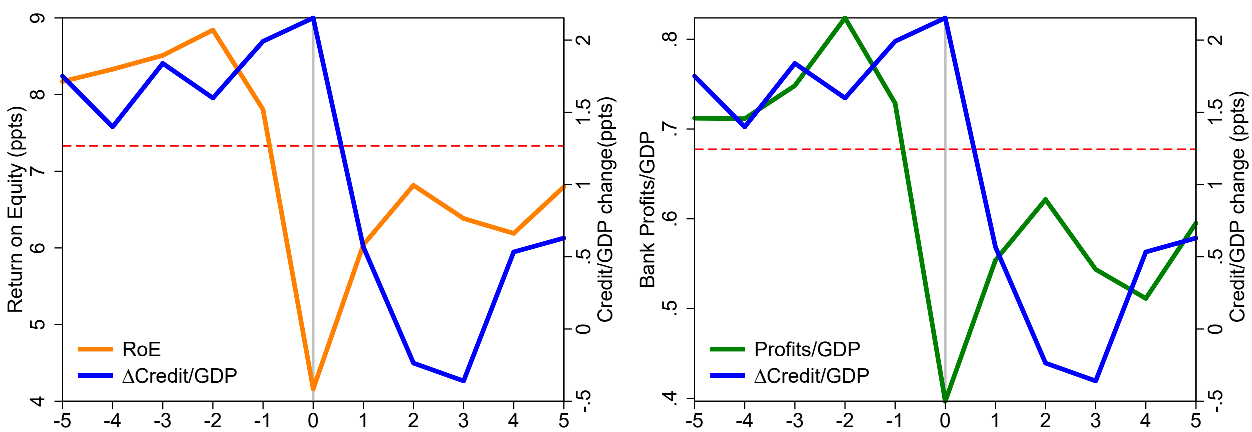
Table A1.10: *Channels – alternative specifications*

	Dependent variable: $\Delta_3 y_{it+3}$					
	Uses of profits		Profit path			
	(1)	(2)	(3)	(4)	(5)	(6)
DoE_{it-1}	0.84***	0.75***				
	(0.23)	(0.23)				
$REToE_{it-1}$		0.47***				
		(0.09)				
$RoA_{i,t-1}$			2.65***	4.17***		
			(0.80)	(1.18)		
$\Delta_3 RoA_{it-1}$			3.51***	1.98***		
			(0.73)	(0.50)		
$Profits\ to\ GDP_{i,t-1}$					3.56***	3.04***
					(1.20)	(1.00)
$\Delta_3 Profits\ to\ GDP_{i,t-1}$					4.37***	3.65***
					(0.86)	(0.59)
R^2	0.136	0.180	0.067	0.142	0.109	0.156
Country fixed effects	✓	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓		✓		✓
Control variables	✓	✓		✓		✓
Observations	979	979	1462	1462	1462	1462

Notes: This table reports regressions of credit-to-GDP changes from t to $t+3$ on levels and three-year changes in banking sector profitability measures. Columns (1) and (2) focus on the uses of profits and decompose $RoE_{i,t-1}$ into dividends over equity ($DoE_{i,t-1}$) and retained earnings over equity ($REToE_{i,t-1}$). Columns (3) to (6) study the profit path and include both, the level of profit measures ($RoA_{i,t-1}$, $Profits\ to\ GDP_{i,t-1}$) and the change ($\Delta_3 RoA_{i,t-1}$, $\Delta_3 Profits\ to\ GDP_{i,t-1}$) in the same regression. Columns (1), (2), (4) and (6) control for three lags of credit-to-GDP changes and a vector of net-worth and macroeconomic control variables (see text in section 3). All specifications include country fixed effects. Standard errors in parentheses are dually clustered on country and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

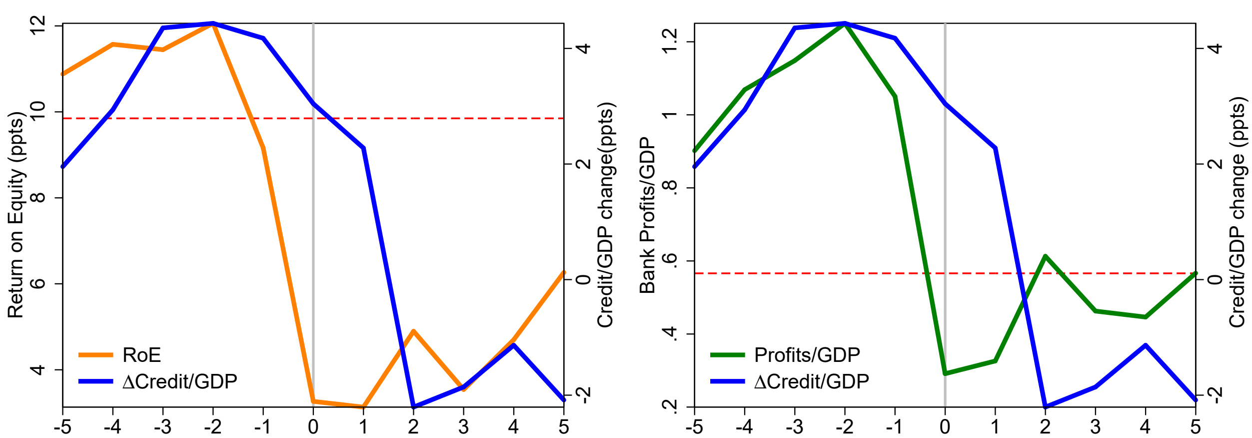
A2. Robustness: profitability around financial crises

Figure A2.2: *Profit variables around financial crisis dates – pre WW2 sample*



Notes: These figures display the evolution of credit and profit variables around a financial crisis before 1939. 0 refers to a year in which a financial crisis starts. Blue (solid) lines display the mean of changes credit/GDP around crises. The orange line displays *RoE* around crises, the green line the ratio of bank profits to GDP. Red (dashed) lines present the full sample average for the respective variable. All variables are expressed in percentage points.

Figure A2.3: *Profit variables around financial crisis dates – post WW2 sample*



Notes: These figures display the evolution of credit and profit variables around a financial crisis after 1945. 0 refers to a year in which a financial crisis starts. Blue (solid) lines display the mean of changes credit/GDP around crises. The orange line displays *RoE* around crises, the green line the ratio of bank profits to GDP. Red (dashed) lines present the full sample average for the respective variable. All variables are expressed in percentage points.

Table A2.11: *Multivariate probit models for systemic financial crises*

	RoE	RoA	Loan Losses/Loans	Profits/GDP
	(1)	(2)	(3)	(4)
$\Delta_{t-2 \to t-1}$	-0.07**	-0.98**	0.60	-0.82*
	(0.03)	(0.43)	(0.53)	(0.46)
$\Delta_{t-3 \to t-2}$	0.13*	2.03***	0.14	2.20**
	(0.07)	(0.57)	(0.66)	(0.87)
$\Delta_{t-4 \to t-3}$	0.11***	2.27***	-2.49***	2.35***
	(0.04)	(0.57)	(0.58)	(0.52)
$\Delta_{t-5 \to t-4}$	0.07	1.58***	-1.95***	1.62***
	(0.05)	(0.58)	(0.45)	(0.55)
$\Delta_{t-6 \to t-5}$	0.09**	1.76***	-1.67***	1.60***
	(0.04)	(0.40)	(0.48)	(0.30)
Credit Growth	✓	✓	✓	✓
AUROC	0.75	0.75	0.76	0.77
Number of Crises	55	56	40	55
Observations	1634	1647	909	1622

Notes: The table shows probit classification models where the dependent variable is a financial crisis dummy and five lags of different profitability measures are used as predictors. In column (1) the predictor is the change in return on equity, in column (2) the change in return on assets, in column (3) the change in loan losses/loans and in column (4) the change in profits/GDP. All models include country fixed effects and the 5-year change in the ratio of credit to GDP. Coefficients are marginal effects. Country clustered standard errors in parentheses. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

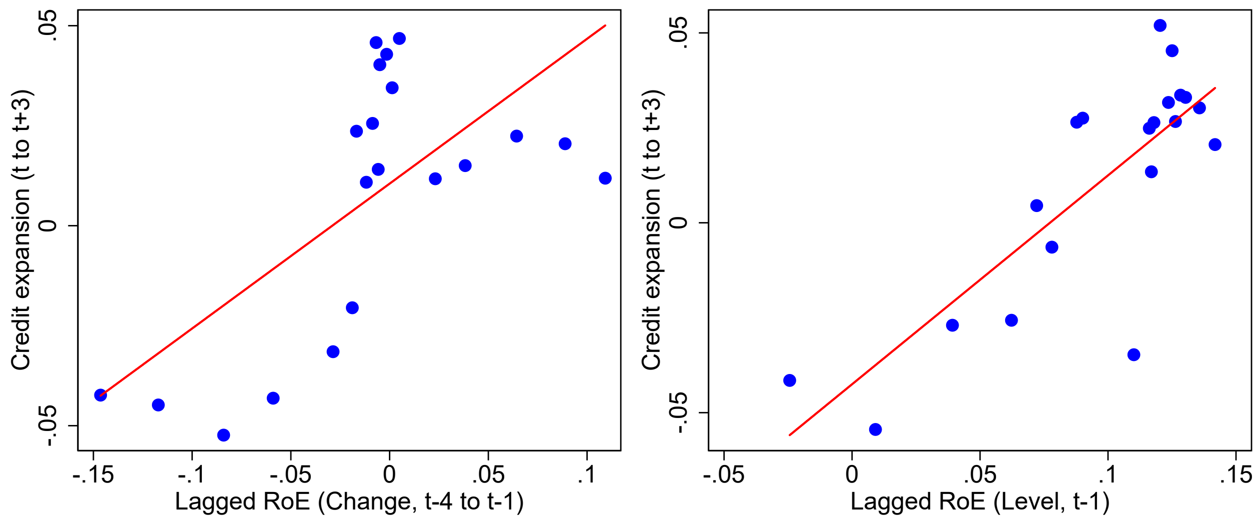
Table A2.12: *Models for changes in credit-to-GDP, subsample of crisis observations*

	(1)	(2)	(3)	(4)
$\Delta_3 RoE_\tau$	0.72***		0.49**	
	(0.12)		(0.17)	
RoE_τ		0.92***		0.77***
		(0.17)		(0.18)
Distributed lag in Δy			✓	✓
Net-worth controls			✓	✓
R^2	0.22	0.33	0.29	0.40
Observations	60	60	60	60

Notes: This table reports regressions of credit-to-GDP changes from τ to $\tau + 3$ on $RoE_{i,\tau}$ and $\Delta_3 RoE_{i,\tau}$, where we restrict the sample to one observation per financial crisis episode and time τ is one year after the start of a crisis. Columns (3) and (4) include net-worth controls, thre year GDP growth and the lagged dependent variable. Standard errors in parentheses are clustered at the country level. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

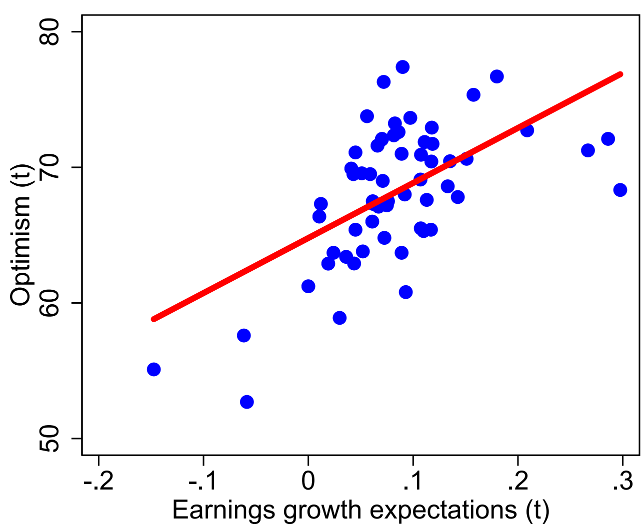
A3. Robustness: survey on earnings expectations

Figure A3.4: *Confirmation of main result: the profit-credit cycle in quarterly US data*



Notes: The figure relates bank profitability and subsequent three-year changes in credit to GDP. Observations are collapsed into 20 equal sized bins according to their profitability (or changes therein). Each point represents the group specific means of profitability and credit expansion. Fitted regression lines illustrate the correlation between bank profitability and subsequent credit growth.

Figure A3.5: *Earnings growth expectations and bank CFO optimism*



Notes: The figure shows the relationship between bank CFO optimism and bank CFO earnings growth expectations. Fitted regression lines illustrate the correlation between the two variables.

A4. Robustness: bank level evidence

Table A4.13: *Multivariate models for credit growth, bank level data, loan losses*

	Dependent variable: $\Delta_3 y_{it+3}$					
	(1) Full	(2) Full	(3) Full	(4) No-overlap	(5) No-overlap	(6) No-overlap
$\Delta_3 LoE_{it-1}$	-0.99***		-1.10***	-1.80***		-1.72***
	(0.20)		(0.20)	(0.59)		(0.50)
LoE_{it-1}		-0.77**	0.24		-1.83**	-0.17
		(0.36)	(0.41)		(0.92)	(0.97)
$Capital\ Ratio_{it-1}$	-0.38***	-0.41***	-0.38**	-0.33*	-0.38**	-0.33*
	(0.15)	(0.15)	(0.15)	(0.18)	(0.18)	(0.18)
$\Delta_3 Capital_{it-1}$	0.04***	0.04***	0.04***	0.04**	0.04***	0.04**
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Bank fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓
Control variables	✓	✓	✓	✓	✓	✓
R^2	0.20	0.20	0.20	0.21	0.21	0.21
Observations	178605	178605	178605	56122	56122	56122

Notes: This table reports regression results from estimating variants of Equation 12 using US Call Report data. The dependent variable $\Delta_3 y_{it+3}$ is the three year change of bank credit (net loans and leases). The main explanatory variables are the lagged 3-year change and the lagged level of loan losses over equity (LoE). All variables are winsorized at the 2.5% level. Columns (1), (2) and (3) report results for all years. Column (4), (5) and (6) restrict the data to non-overlapping observations only. All specifications also include bank and year fixed effects. Standard errors in parentheses are dually clustered on bank and year. *,**,*** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

B. Data appendix

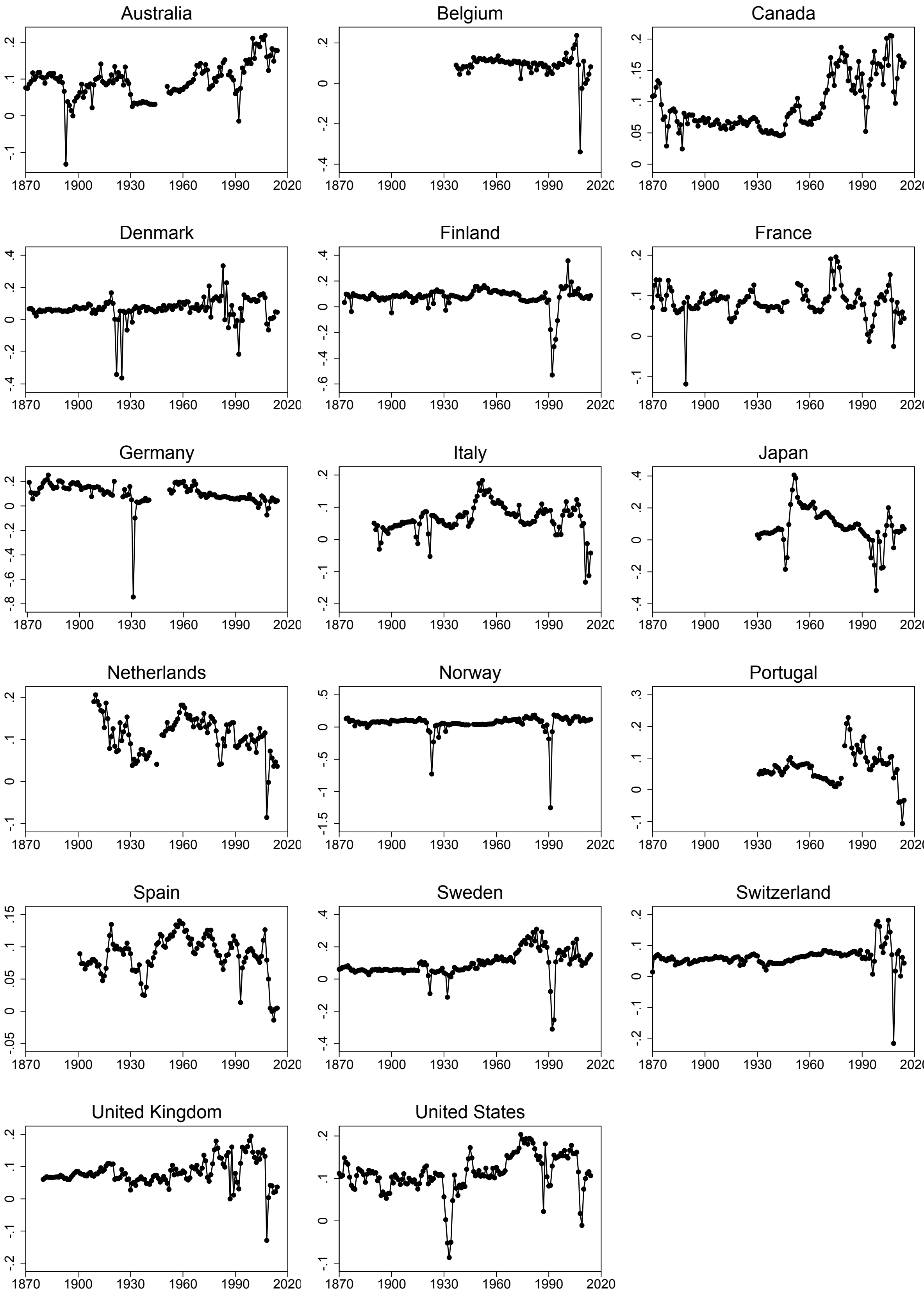
This appendix details the sources of our banking sector profitability estimates for each country. The database is built around an aggregate profitability series for the banking system and decomposes this profitability into its sources. It includes separate time series for bank return on assets and its main components - revenue (net interest income + net fee income), operating expenses and loan losses. All variables are constructed relative to total assets of the financial system. Items are then rescaled using leverage data from Jordà et al. (2017a) (JRST henceforth). We use end of year total capital and total liabilities as denominators in the calculation.

Table B.1: *Variable definitions*

Item	Description
Return on equity	After tax profitability of the banking system relative to end of year equity.
Return on assets	After tax profitability of the banking system relative to end of year assets.
Dividends	Total dividends of the banking system relative to end of year assets.
Costs	Operating expenses of the banking system relative to end of year assets.
Revenues	Total revenue (net interest income + net fee income) relative to end of year assets.
Loan losses	Loan loss item in the bank income statement relative to end of year assets (charge-offs or provisions for charge-offs).

Our primary goal is across series and within country consistency. We use growth rate splicing if there are significant inconsistencies across sources and coverage, but aim to keep original data levels as much as possible. Maintaining original levels has the advantage that it allows for an bias free construction of ratios and manipulations of the individual series (for example when considering the revenue to cost relationship). Figure B.1 displays the main profitability series – return on equity – on a country by country basis.

Figure B.1: *Return on Equity*



A1. Summary statistics

Table B.2: *Summary Statistics*

	Obs.	Mean	S.D.	Min	Max
Return on Equity	2131	8.38	7.25	-125.36	40.57
Return on Assets	2148	0.77	0.75	-7.71	5.27
Δ_3 RoE	2060	-0.09	8.42	-118.19	142.38
Δ_3 RoA	2076	-0.04	0.62	-8.63	7.95
Dividends over Equity	1344	5.55	2.51	-4.28	20.88
Retained Earnings over Equity	1342	2.60	7.16	-125.52	30.95
Capital Ratio	2232	10.37	7.48	0.85	46.86
Credit to GDP	2257	56.40	35.38	0.47	204.52
Δ_3 Credit to GDP	2173	2.27	8.71	-56.09	53.08
Winsorized income data (2.5% level)					
Return on Equity	2131	8.67	4.81	-3.97	20.01
Return on Assets	2148	0.78	0.59	-0.26	2.54
Δ_3 RoE	2060	-0.13	4.42	-13.83	11.28
Δ_3 RoA	2076	-0.04	0.38	-1.21	1.00
Dividends over Equity	1344	5.53	2.29	1.32	12.38
Retained Earnings over Equity	1342	2.85	4.30	-10.24	12.90

Notes: All variables in percentage points.

Australia

Table B.3: *Data sources: Australia*

Year	Data source
Bank profitability	
1870–1944	Butlin, Hall and White (1971). Australian banking and monetary statistics, 1817-1945. Reserve Bank of Australia Occasional Paper No. 4A.
1946–1970	White (1973). Australian banking and monetary statistics 1945-1970. Reserve Bank of Australia Occasional Paper No. 4B. Major trading banks.
1971–1980	Statistical Yearbook (various years). Data for joint stock banks.
1981–2001	OECD Banking Statistics. Income statement and balance sheet.
2002–2003	Annual Reports of the four major banks (various years): ANZ, NAB, Commonwealth Bank and Westpac.
2004–2015	Australian Prudential Regulation Authority (2016). Quarterly ADI performance statistics.
Bank P&L components	
1946–1970	White (1973). Australian banking and monetary statistics 1945-1970. Reserve Bank of Australia Occasional Paper No. 4B. Major trading banks.
1963–1974	Statistical Yearbook (various years). Data for joint stock banks.
1981–2001	OECD Banking Statistics. Income statement and balance sheet.
2004–2015	Australian Prudential Regulation Authority (2016). Quarterly ADI performance statistics.
Bank dividends	
1870–1944	Butlin, Hall and White (1971). Australian banking and monetary statistics, 1817-1945. Reserve Bank of Australia Occasional Paper No. 4A.
1946–1974	White (1973). Australian banking and monetary statistics 1945-1970. Reserve Bank of Australia Occasional Paper No. 4B. Major trading banks.
1981–2001	OECD Banking Statistics. Income statement and balance sheet.

Belgium

Table B.4: *Data sources: Belgium*

Year	Data source
Bank profitability	
1937–1980	Rapport Annuel de la Commission Bancaire (various years). All banks for 1944 to 1980 and large banks for 1937 to 1943.
1983–1999	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
2000–2017	National Bank of Belgium (various years). Financial Stability Report. All credit institutions.
Bank P&L components	
1981–2009	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
2010–2017	National Bank of Belgium (various years). Financial Stability Report. All credit institutions.
Bank dividends	
1981–2009	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.

Canada

Table B.5: *Data sources: Canada*

Year	Data source
Bank profitability	
1870–1967	Annual Reports of major banks (various years): Bank of Montreal, Scotiabank, Canadian Bank of Commerce, Royal Bank of Canada, Bank of Toronto, Dominion Bank, Toronto Dominion Bank (after merger).
1968–1981	Bank of Canada Review (various years). Table A4 of the February or March issue.
1982–2008	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
2009–2015	Canadian Bankers Association. Database of Domestic Banks' Financial Results. Fiscal year-end 2006-2015, 8 banks.
Bank P&L components	
1929–1967	Historical Statistics of Canada. Link: https://www150.statcan.gc.ca/n1/pub/11-516-x/3000140-eng.htm. Tables J181-201 and J261-272.
1968–1981	Bank of Canada Review (various years). Table A4 of the February or March issue.
1982–2009	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
2010–2015	Canadian Bankers Association. Database of Domestic Banks' Financial Results. Fiscal year-end 2006-2015, 8 banks.
Bank dividends	
1870–1963	Annual Reports of major banks (various years): Bank of Montreal, Scotiabank, Canadian Bank of Commerce, Royal Bank of Canada, Bank of Toronto, Dominion Bank, Toronto Dominion Bank (after merger).
1964–1967	Historical Statistics of Canada. Link: https://www150.statcan.gc.ca/n1/pub/11-516-x/3000140-eng.htm. Tables J181-201 and J261-272.
1968–1987	Bank of Canada Review (various years). Table A4 of the February or March issue.
1988–2009	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
2010–2015	Canadian Bankers Association. Database of Domestic Banks' Financial Results. Fiscal year-end 2006-2015, 8 banks.

Denmark

Table B.6: *Data sources: Denmark*

Year	Data source
Bank profitability	
1872–1920	Danmarks Statistik (1969). Statistike Underslogelser Nr. 24 Kreditmarkedsstatistik. Link: http://www.dst.dk/Site/Dst/Udgivelser/GetPubFile.aspx?id=19918&sid=kreditm. Table: Bankernes samlede status inden for hovedlandsdele og for hele landet.
1921–1985	Statistical Yearbook (various years).
1986–2009	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
2010–2015	Finansrdet (2015). The sector in figures. Table: Accounting figures.
Bank P&L components	
1875–1920	Abildgren (2017). A chart & data book on the monetary and financial history of Denmark. Working Paper. Sheet S081A
1920–1978	Statistical Yearbook (various years).
1979–2009	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
2010-2015	Finansrdet (2015). The sector in figures. Table: Accounting figures.
Bank dividends	
1872–1920	Danmarks Statistik (1969). Statistike Underslogelser Nr. 24 Kreditmarkedsstatistik. Link: http://www.dst.dk/Site/Dst/Udgivelser/GetPubFile.aspx?id=19918&sid=kreditm. Table: Bankernes samlede status inden for hovedlandsdele og for hele landet.
1921–1978	Beretning om de danske bankers virksomhed (various years). Official government publication with statistics on all commercial banks.
1979–2004	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.

Finland

Table B.7: *Data sources: Finland*

Year	Data source
Bank profitability	
1870–2010	Herrala (1999). Banking crises vs depositor crises: the era of the finnish markka. Scandinavian Economic History Review. Vol 47, No 2, 5-22. Banking sector balance sheets and income statements in Finland: selected figures. Data continued by the author for the latter years. Data kindly shared by the author.
2011–2016	Statistics Finland Online. Link: http://pxnet2.stat.fi/PXWeb/pxweb/fi/StatFin_Passiivi/StatFin_Passiivi__rah__llai/. Change website to Finnish to access data prior to 2014.
Bank P&L components	
1870–1990	Herrala (1999). Banking crises vs depositor crises: the era of the finnish markka. Scandinavian Economic History Review. Vol 47, No 2, 5-22. Banking sector balance sheets and income statements in Finland: selected figures. Data continued by the author for the latter years. Data kindly shared by the author.
1991–2000	Statistical Yearbook of Finland (various years). Talletuspankit, Dopositionsbanker (deposit taking institutions).
2001–2016	Statistics Finland Online. Link: http://pxnet2.stat.fi/PXWeb/pxweb/fi/StatFin_Passiivi/StatFin_Passiivi__rah__llai/. Change website to Finnish to access data prior to 2014.
Bank dividends	
1870–1955	Aaku (1957). Suomen Liikepankit 1862-1955. Commercial banks.
1979–2009	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.

France

Table B.8: *Data sources: France*

Year	Data source
Bank profitability	
1870–1914	Bouvier, Furet and Gillet (1965). Le mouvement du profit en France au 19e sicle. Paris et La Haye. Data of individual banks is aggregated.
1915–1947	Annual Reports of major banks (various years): Credit Lyonnais and Societe Generale.
1953–1980	Commission de controle de banques (various years). Rapport Annuel.
1980–2009	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
2010–2015	European Central Bank Online. Consolidated banking data. Link: https://www.ecb.europa.eu/stats/supervisory_prudential_statistics/consolidated_banking_data/html/index.en.html. Domestic banking groups and stand alone banks, foreign (EU and non-EU) controlled subsidiaries and foreign (EU and non-EU) controlled branches.
Bank P&L components	
1980–2006	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
2007–2015	European Central Bank Online. Consolidated banking data. Link: https://www.ecb.europa.eu/stats/supervisory_prudential_statistics/consolidated_banking_data/html/index.en.html. Domestic banking groups and stand alone banks, foreign (EU and non-EU) controlled subsidiaries and foreign (EU and non-EU) controlled branches.
Bank dividends	
1870–1913	Bouvier, Furet and Gillet (1965). Le mouvement du profit en France au 19e sicle. Paris et La Haye. Data of individual banks is aggregated.
1988–2009	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.

Germany

Table B.9: *Data sources: Germany*

Year	Data source
Bank profitability	
1871–1882	Annual Reports of major banks (various years): Commerzbank and Deutsche Bank for 1871-1872, Commerzbank, Dresdener Bank and Deutsche Bank for 1873-1882.
1883–1920	Die Deutschen Banken im Jahre (various years). Special publication of 'Der Oekonomist'. Covers largest 50-150 commercial banks.
1925–1944	Annual Reports of major banks (various years): Commerzbank, Dresdener Bank and Deutsche Bank.
1952–1968	Annual Reports of major banks (various years): Commerzbank and Deutsche Bank.
1969–2016	Bundesbank Online. Statistics of banks' profit and loss accounts. Link: https://www.bundesbank.de/Navigation/EN/Statistics/Banks_and_other_financial_institutions/Banks/Statistics_of_the_banks_profit_and_loss_accounts/tables/tabellen.html. Table guv_tab8_en.
Bank P&L components	
1883–1920	Die Deutschen Banken im Jahre (various years). Special publication of 'Der Oekonomist'. Covers largest 50-150 commercial banks.
1969–2016	Bundesbank Online. Statistics of banks' profit and loss accounts. Link: https://www.bundesbank.de/Navigation/EN/Statistics/Banks_and_other_financial_institutions/Banks/Statistics_of_the_banks_profit_and_loss_accounts/tables/tabellen.html. Table guv_tab8_en.
Bank dividends	
1883–1920	Die Deutschen Banken im Jahre (various years). Special publication of 'Der Oekonomist'. Covers largest 50-150 commercial banks.
1979–2009	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.

Italy

Table B.10: *Data sources: Italy*

Year	Data source
Bank profitability	
1890–1973	Natoli, Piselli, Triglia and Vercelli (2016). Historical archive of credit in Italy. Bank of Italy, Economic History Working Papers No. 36.
1974–1992	Annual report of the Bank of Italy (various years).
1993–2009	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
2010–2015	Bank of Italy – Statistical Database. Link: https://www.bancaditalia.it/statistiche/basi-dati/bds/index.html?com.dotmarketing.htmlpage.language=1. All banks.
Bank P&L components	
1974–1992	Annual report of the Bank of Italy (various years).
1993–2009	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
2010–2015	Bank of Italy – Statistical Database. Link: https://www.bancaditalia.it/statistiche/basi-dati/bds/index.html?com.dotmarketing.htmlpage.language=1. All banks.
Bank dividends	
1984–2009	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
2010–2015	Bank of Italy – Statistical Database. Link: https://www.bancaditalia.it/statistiche/basi-dati/bds/index.html?com.dotmarketing.htmlpage.language=1. All banks.

Japan

Table B.11: *Data sources: Japan*

Year	Data source
Bank profitability	
1930–1956	Economic Statistics Annual (1972). Statistics Department, Bank of Japan. Ordinary banks.
1957–1979	Bank of Japan, File CDAB0540. Ordinary Banks.
1980–2008	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
2009–2015	IMF Online. Financial Soundness Indicators. Link: data.imf.org/FSI.
Bank P&L components	
1930–1956	Economic Statistics Annual (1972). Statistics Department, Bank of Japan. Income and expenses of ordinary banks.
1956–1979	Bank of Japan, File CDAB0540. Ordinary Banks.
1980–2008	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
Bank dividends	
1980–2008	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.

Netherlands

Table B.12: *Data sources: Netherlands*

Year	Data source
Bank profitability, P&L components and dividends	
1870–1941	Annual Reports of major banks (various years): 1909-1941: Incassobank, Rotterdamsche Bank, Amsterdamsche Bank, Twentsche Bank. 1877-1908: Twentsche Bank, Ontvang- en Betaalkas, Handel en Maatschappij. 1870-1976: Twentsche Bank. Sources: Eisfeld (1916). Das Niederlndische Bankwesen. Den Haag. Kiliani (1923). Die Grobanken Entwicklung in Holland und die Mitteleuropische Wirtschaft. Verlag von Felix Meiner in Leipzig. De Graaf (2012). Voor Handel en Maatschappij – Geschiedenis van de Nederlandsche Handel-Maatschappij, 1824-1964.
1948–1980	Centraal Bureau voor de Statistiek (various years). Maandstatistiek van het financiewezen. Commercial banks.
1981–2008	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
2008–2017	De Nederlandsche Bank Online. Link: https://statistiek.dnb.nl/en/downloads/index.aspx#/details/balance-sheet-of-the-dutch-banking-sector-consolidated/dataset/dcb6775e-1afa-4a45-bee0-669be22f8bd5/resource/ebb838b3-fe5f-422d-b6b2-2021ba06b4c98. Balance sheet and income statement of the Dutch banking sector.

Norway

Table B.13: *Data sources: Norway*

Year	Data source
Bank profitability and dividends	
1874–1944	Statistics Norway Online. Various publications. Link: https://www.ssb.no/a/en/histstat/, section 13. Money and credit – Norges private aksjebanker og sparebanker.
1947–1975	Statistical Yearbook of Norway (various years). Forretningsbanker. Driftsregnskap.
1976–1980	Statistical Yearbook of Norway (various years). Offentlige og private banker. Resultatregnskap. Norske forretningsbanker og Norges sparebanker.
1980–2008	OECD Banking Statistics. Income statement and balance sheet. Online Database.
2010–2017	Statistics Norway Online. Link: https://www.ssb.no/en/statbank/table/07880/tableViewLayout1/?rxid=e8526cc9-a688-4b75-857d-2c79e5112586.
Bank P&L components	
1900–1944	Statistics Norway Online. Various publications. Link: https://www.ssb.no/a/en/histstat/, section 13. Money and credit – Norges private aksjebanker og sparebanker.
1976–1980	Statistical Yearbook of Norway (various years). Offentlige og private banker. Resultatregnskap. Norske forretningsbanker og Norges sparebanker.
1980–2008	OECD Banking Statistics. Income statement and balance sheet. Online Database.
2010–2017	Statistics Norway Online. Link: https://www.ssb.no/en/statbank/table/07880/tableViewLayout1/?rxid=e8526cc9-a688-4b75-857d-2c79e5112586.

Portugal

Table B.14: *Data sources: Portugal*

Year	Data source
Bank profitability	
1931–1961	Instituto Nacional de Estatistica, Estatisticas Financeiras (various issues). Bancos, Casas Bancarias e Caixas Economicas.
1962–1978	Instituto Nacional de Estatistica, Estatisticas Monetaria Financeiras (various issues). Group of Bancos e casas bancario less Banco Formento and Bank of Portugal.
1980–2007	OECD Banking Statistics. Income statement and balance sheet. Online Database.
2008–2016	European Central Bank Online. Consolidated banking data. Link: https://www.ecb.europa.eu/stats/supervisory_prudential_statistics/consolidated_banking_data/html/index.en.html. Domestic banking groups and stand alone banks, foreign (EU and non-EU) controlled subsidiaries and foreign (EU and non-EU) controlled branches.
Bank P&L components	
1980–2007	OECD Banking Statistics. Income statement and balance sheet. Online Database.
2008–2016	European Central Bank Online. Consolidated banking data. Link: https://www.ecb.europa.eu/stats/supervisory_prudential_statistics/consolidated_banking_data/html/index.en.html. Domestic banking groups and stand alone banks, foreign (EU and non-EU) controlled subsidiaries and foreign (EU and non-EU) controlled branches.

Spain

Table B.15: *Data sources: Spain*

Year	Data source
Bank profitability	
1901–1978	Tafunell (2000). La rentabilidad financiera de la empresa espaola, 1880-1981: una estimacin en perspectiva sectorial. Revista de Historia Industrial 18: 71-112.
1979–2009	OECD Banking Statistics. Income statement and balance sheet. Online Database.
2010–2015	European Central Bank Online. Consolidated banking data. Link: https://www.ecb.europa.eu/stats/supervisory_prudential_statistics/consolidated_banking_data/html/index.en.html. Domestic banking groups and stand alone banks, foreign (EU and non-EU) controlled subsidiaries and foreign (EU and non-EU) controlled branches.
Bank P&L components	
1979–2007	OECD Banking Statistics. Income statement and balance sheet. Online Database.
2008–2015	European Central Bank Online. Consolidated banking data. Link: https://www.ecb.europa.eu/stats/supervisory_prudential_statistics/consolidated_banking_data/html/index.en.html. Domestic banking groups and stand alone banks, foreign (EU and non-EU) controlled subsidiaries and foreign (EU and non-EU) controlled branches.
Bank dividends	
1979–2007	OECD Banking Statistics. Income statement and balance sheet. Online Database.

Sweden

Table B.16: *Data sources: Sweden*

Year	Data source
Bank profitability and dividends	
1870–1997	Swedish Riksbank. Bank Lending and Borrowing 1870-2006. Data source: Hortlund (2005). The long-term relationship between capital and earnings in banking. SSE/EFI Working Paper Series in Economics and Finance No. 611.
1997–2015	Statistics Sweden Online. Link: http://www.statistikdatabasen.scb.se/pxweb/en/ssd/START__FM__FM0402/?rxid=3d618be3-5da4-4cb7-9934-972462441227. Financial Markets – Financial Enterprises. Balance sheets and income statement for all banks.
Bank P&L components	
1870–1997	Swedish Riksbank. Bank Lending and Borrowing 1870-2006. Data source: Hortlund (2005). The long-term relationship between capital and earnings in banking. SSE/EFI Working Paper Series in Economics and Finance No. 611.
1988–1995	Riksbank Yearbook (various years). Banking sector balance sheets and profit and loss account. Available funds and their distribution. All banks.
1997–2015	Statistics Sweden Online. Link: http://www.statistikdatabasen.scb.se/pxweb/en/ssd/START__FM__FM0402/?rxid=3d618be3-5da4-4cb7-9934-972462441227. Financial Markets – Financial Enterprises. Balance sheets and income statement for all banks.

Switzerland

Table B.17: *Data sources: Switzerland*

Year	Data source
Bank profitability and dividends	
1870–1905	Historical Statistics of Switzerland Online. Link: https://www.fsw.uzh.ch/histstat/main.php. Table O.12. Diskontobanken, Kantonalbanken und brige Emissionsbanken: Passiven, Aktiven und Gewinnrechnung 1826-1910.
1906–2002	Schweizerische Nationalbank. Historische Zeitreihen. Die Banken in der Schweiz. Link: https://www.snb.ch/de/iabout/stat/statrep/statpubdis/id/statpub_histz_arch. Balance sheet data from Table 9. Net profit after taxes from Tables 29.1 and 29.2.
1996–2016	Schweizerische Nationalbank Online. Link: https://data.snb.ch. Annual banking statistics. All banks.
Bank P&L components	
1870–1905	Historical Statistics of Switzerland Online. Link: https://www.fsw.uzh.ch/histstat/main.php. Table O.12. Diskontobanken, Kantonalbanken und brige Emissionsbanken: Passiven, Aktiven und Gewinnrechnung 1826-1910.
1906–1995	Schweizerische Nationalbank. Historische Zeitreihen. Die Banken in der Schweiz. Link: https://www.snb.ch/de/iabout/stat/statrep/statpubdis/id/statpub_histz_arch. Balance sheet data from Table 9. Income components from Tables 29.1 and 29.2.
1906–1992	Historical Statistics of Switzerland Online. Link: https://www.fsw.uzh.ch/histstat/main.php. Table O.15. Banken (1): Gewinn- und Verlustrechnung 1906-1992.
1993–1995	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues. All banks.
1996–2016	Schweizerische Nationalbank Online. Link: https://data.snb.ch. Annual banking statistics. All banks.

United Kingdom

Table B.18: *Data sources: United Kingdom*

Year	Data source
Bank profitability, P&L components and dividends	
1870–1920	Capie and Webber (1985). Profits and profitability in british banking, 1870-1939. Centre for Banking and International Finance Discussion Paper 18. Series: English and Welsh Joint Stock Banks – Aggregate Profits.
1920–1967	Capie and Billings (2004). Evidence on competition in English commercial banking, 1920-1970. Financial History Review. Volume 11 / Issue 01 / pp 69 - 103.
1968	Ackrill and Hannah (2001). Barclays, The Business of Banking 1690-1996. Cambridge University Press. Tables B1, B2, B4, B6.
1969–1976	CLCB Statistical Unit. London Clearings Banks 1966-1976. Profit and balance sheet statistics. Consolidated accounts.
1977–1979	Ackrill and Hannah (2001). Barclays, The Business of Banking 1690-1996. Cambridge University Press. Tables B1, B2, B4, B6.
1980–2008	OECD Banking Statistics. Income statement and balance sheet. Online Database and print issues.
2009–2015	European Central Bank Online. Consolidated banking data. Link: https://www.ecb.europa.eu/stats/supervisory_prudential_statistics/consolidated_banking_data/html/index.en.html. Domestic banking groups and stand alone banks, foreign (EU and non-EU) controlled subsidiaries and foreign (EU and non-EU) controlled branches.

United States

Table B.19: *Data sources: United States*

Year	Data source
Bank profitability	
1870–1918	Historical Statistics of the United States. Link: https://hsus.cambridge.org/HSUSWeb/HSUSEntryServlet. Table: National banks number, earnings, and expenses: 1869-1998 Cj238-250.
1919–1950	Banking and Monetary Statistics 1914-1941 and 1941-1970. Tables: Member bank earnings, expenses and dividends, 1919-1941. Member bank income, expenses and dividends 1941-70. All FDIC insured commercial banks.
1951–2015	FDIC Online. Historical Statistics on Banking. Link: https://www5.fdic.gov/hsob/HSOBRpt.asp. All FDIC insured commercial banks.
Bank P&L components	
1870–1935	Historical Statistics of the United States. Link: https://hsus.cambridge.org/HSUSWeb/HSUSEntryServlet. Table: National banks number, earnings, and expenses: 1869-1998 Cj238-250.
1935–1966	FDIC Online. Historical Statistics on Banking. Link: https://www5.fdic.gov/hsob/HSOBRpt.asp. All FDIC insured commercial banks.
1967–2015	FDIC Online. Historical Statistics on Banking. Link: https://www5.fdic.gov/hsob/HSOBRpt.asp. All FDIC insured commercial banks.
Bank dividends	
1870–1918	Historical Statistics of the United States. Link: https://hsus.cambridge.org/HSUSWeb/HSUSEntryServlet. Table: National banks number, earnings, and expenses: 1869-1998 Cj238-250.
1919–1945	Banking and Monetary Statistics 1914-1941 and 1941-1970. Tables: Member bank earnings, expenses and dividends, 1919-1941. Member bank income, expenses and dividends 1941-70. All FDIC insured commercial banks.
1946–1966	FDIC Online. Historical Statistics on Banking. Link: https://www5.fdic.gov/hsob/HSOBRpt.asp. All FDIC insured commercial banks.
1967–2015	FDIC Online. Historical Statistics on Banking. Link: https://www5.fdic.gov/hsob/HSOBRpt.asp. All FDIC insured commercial banks.

A2. Systemic banking crises

Dates of systemic banking crises are based on Jordà et al. (2017b).

AUS: 1893, 1989.
BEL: 1870, 1885, 1925, 1931, 1934, 1939, 2008.
CAN: 1907.
CHE: 1870, 1910, 1931, 1991, 2008.
DEU: 1873, 1891, 1901, 1907, 1931, 2008.
DNK: 1877, 1885, 1908, 1921, 1931, 1987, 2008.
ESP: 1883, 1890, 1913, 1920, 1924, 1931, 1978, 2008.
FIN: 1878, 1900, 1921, 1931, 1991.
FRA: 1882, 1889, 1930, 2008.
GBR: 1890, 1974, 1991, 2007.
ITA: 1873, 1887, 1893, 1907, 1921, 1930, 1935, 1990, 2008.
JPN: 1871, 1890, 1907, 1920, 1927, 1997.
NLD: 1893, 1907, 1921, 1939, 2008.
NOR: 1899, 1922, 1931, 1988.
PRT: 1890, 1920, 1923, 1931, 2008.
SWE: 1878, 1907, 1922, 1931, 1991, 2008.
USA: 1873, 1893, 1907, 1929, 1984, 2007.